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User Association Algorithm with Optimal Bandwidth Allocation for Energy Efficiency Optimization in 5G HetNet

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***Abstract*—** A user association algorithm with optimal bandwidth allocation for optimizing the energy efficiency of HetNet is presented in this paper. The energy efficiency of the network was formulated as a non-convex optimization problem due to the binary nature of the user association indicator. The Lagrangian dual decomposition and sub-gradient method were used to maximize energy efficiency. The performance of the developed algorithm was compared with Maximum Reference Signal Received Power (MaxRSRP) and Maximum Signal-to-Interference-Noise Ratio (MaxSINR) user associations which are the benchmark user association algorithms as specified by 3rd Generation Partnership Project. The results show that the proposed algorithm has network energy efficiency performance improvement of 9.94% and 5.45% with respect to MaxRSRP and MaxSINR user association respectively, for increasing number of macro BSs antennas. Also, the proposed algorithm has network energy efficiency performance improvement of 11.33% and 6.65% over MaxRSRP and MaxSINR user association respectively, for increasing number of pico BSs per macro cell. Lastly, the proposed algorithm has network energy efficiency performance improvement of 11.00% and 7.35% over MaxRSRP and MaxSINR user association, respectively, for increasing number of femto BSs per macro cell. This implies that the developed algorithm outperforms the existing algorithms in terms of network energy efficiency.

***Keywords*—** Beamforming, HetNet, Massive MIMO, mmWave, Resource allocation, User association.

I. INTRODUCTION

A wireless network statistics in 2016 showed that global mobile traffic will increase by sevenfold between 2016 and 2021. This corresponds to the mobile data traffic compound annual growth rate of 46%. This increase was from 26% smartphones of the total global mobile devices which were responsible for 88% of the total mobile data traffic. In fact, it has been forecasted that in 2021 mobile networks connected devices will be largely smart devices [1]. This growth in the usage of high-speed devices such as tablets smartphones, etc. has resulted in the exponential growth in multimedia (mobile video) traffic from the proliferation of multimedia infotainment applications (for example video conferencing, video streaming, real-time interactive games, etc.) [2]. However, in supporting this rapid increase and enormous data usage, the presented Fourth Generation (4G) Long Term Evolution (LTE) mobile cellular network explores different deployments like Multiple-Input-Multiple-Output (MIMO) antennas and Heterogeneous Networks (HetNets) to improve achievable throughput and capacity. This ongoing traffic explosion is unlikely to be sustained by the 4G LTE cellular network in the long run [3]. Hence, the need for satisfying the exponential rise in mobile data traffic and capacity in mobile broadband communications is unquestionably the main factor that has brought about the development of the future Fifth Generation (5G) cellular mobile network [4]. This is to enable for the provision of multi-gigabits per seconds (Gbps) data rates for each User Equipment (UE) to support high-speed multimedia applications which come with stringent Quality of Service (QoS) requirements such as data-rate, latency etc. [5]. Therefore, the 5G cellular mobile networks are being developed to provide for the anticipated 1000 times data rate increase with reference to 4G cellular mobile

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networks, thus achieving a very high network capacity [4]. To achieve this target, several emerging technologies are being considered for the deployment of the 5G mobile cellular networks such as dense HetNets, massive MIMO antennas, and millimeter wave (mmWave) frequency etc. [3]. However, none of these technologies can solely accomplish 5G requirements [6]. Therefore, the integration of the different technologies for the deployment of the 5G mobile cellular networks is identified as a promising solution [7].

Consequently, there is a need for the 5G network to achieve better cost efficiency to address mobile operators' concerns about revenue flattening. In particular, energy efficiency of the 5G mobile network needs to be improved by a factor of 1,000 compared with that achieved by the 4G mobile network in order to cope with the anticipated 1000x data rate increase [6]. This has made energy efficiency in the last decade to emerge as a new prominent figure of merit due to economic, operational, and environmental concerns [8]. The main general consensus in the wireless academic and industrial communities is that the 1000 times capacity increase must be achieved at a similar or lower power consumption level to the 4G mobile cellular networks [8]. Hence, there is a need for an energy efficient user association scheme for 5G HetNets. User association algorithm plays a key role in enhancing energy efficiency and load balancing of a mobile network; and it is used to determine the BS. A particular UE should be associated with it before data transmission commences [9]. The existing user association algorithms of MaxRSRP association and MaxSINR association, which are the benchmark user association algorithm specified by the 3GPP result in unbalanced loads among BSs in massive MIMO antennas enabled Fifth 5G HetNets and unfair throughput among UEs in the network [2]. This led to the decreased energy efficiency of the network and uncertified Quality of Service (QoS) for active UE. This motivated [10] to develop a distributed fair user association in massive MIMO enabled HetNets to maximize energy efficiency of the network while ensuring the SINR received by the UEs. But, the energy efficiency of this network can be improved by jointly designing the power control algorithm with the user association to update the transmit power of the BSs with respect to traffic load on the BSs for higher network load balancing and energy efficiency. This work was improved by [11] which develop an energy efficient joint optimization algorithm of user association and power control for massive MIMO enabled HetNets for the maximization of the network sum energy efficiency under load constraint of BS. Here, the maximization of the network energy efficiency did not consider the QoS requirements of the UEs. This led to unguaranteed reception throughput of the UEs. Similarly, the maximization of the system sum energy efficiency also resulted in extremely unfair throughput allocation. As can be seen, these researchers focused on deploying one or two of the enabling 5G technologies while developing one or two of the energy efficient radio resource management schemes. These schemes had deployed massive MIMO used digital beamforming at the BSs. This led to an increased power consumption of the BS as a result of digital beamforming using a radio frequency chain per antenna. Furthermore, to achieve better network energy efficiency performance, there is a need to perform a joint user association and power control optimization with optimal bandwidth allocation. Optimizing the bandwidth of the BSs is also the main reason for increasing the network energy efficiency. For the aforementioned reasons, this paper presents an energy-efficient joint user association with optimal bandwidth allocation for 5G HetNets while efficiently employing the advantages of massive MIMO antennas and mmWaves technologies. The energy efficient radio resource algorithm for 5G HetNets employs a hybrid beamforming technique to reduce energy consumption at the massive MIMO BSs.

II. MATHEMATICAL MODELING AND ALGORITHM DEVELOPMENT

A) Channel Modeling

The channel modeling for the microwave and mmWave massive MIMO antennas communication between the UE is done using the geometric channel correlation model. Because of characterizing massive MIMO channels which employs multiple antennas in the transmitter and/or receiver, the correlation between transmit and receive antenna is the vital aspect of massive MIMO channel modeling. This correlation depends on the angle of departure (AoD) and angle of arrival (AoA) of each multiple path components from the BS to the UE, respectively [12]. The microwave and mmWave massive MIMO antennas utilize hybrid beamforming due to its energy efficiency.

Let N represent the number of radio frequency (RF) chain per massive MIMO BS and M the number of antennas per RF chain in massive MIMO BS. This results in NM the number of massive MIMO antennas per massive MIMO BS. Hence, the massive MIMO channel vector from a massive MIMO BS with NM transmitting antennas to the k^{th} single antenna UE is given as [13]:

$$h_k = \sqrt{\frac{1}{\rho}}\sum_{l=1}^{NM} \alpha_l a_t(\theta_l) a_r^{*}(\phi_l) \tag{1}$$

The complex channel gain of the l^{th} path α_l captures the effect of large and small-scale fading on the transmitted signal in the cells. The channel gain is modeled as an independently and identically distributed complex random variable given as $CN(0,1)$ [13]; ρ is the distance-dependent path loss between the BS and UE. It is modeled using the log-normal shadowing model for the mmWave BS; and is given [14] as:

$$\rho(d) = \rho(d_o) + 10\eta \log(d) + \chi_\sigma \tag{2}$$

where the path loss $\rho(d)$ is in dB with is a function of distance and a random variable which is referenced to a free space reference distance d_o. It is modeled by the path loss exponent η and a shadowing random variable χ_σ, which is represented as a Gaussian random variable in dB with zero mean and σ dB standard deviation. Similarly, ρ is modeled for microwave BS using [9] given as:

$$\rho(d) = 15.3 + 37.6\log(d) \tag{3}$$

Where d is the distance of the UE from the BS in the meter.

The number of effective channel paths L is equal to the number of antennas. NM for massive MIMO communication assumes a maximum number of scatters in the propagation path for worst case scenario. The variables $\theta_l \in [0 : \frac{2\pi}{NM} : 2\pi)$ and $\phi_l \in [0 : \frac{2\pi}{NM} : 2\pi)$ are the equally spaced l^{th} path's AoD and AoA of the rays, respectively. The transmit and receive steering vectors for NM transmit antennas and a single antenna UE k are expressed by [15]:

$$a_t(\theta_l)=\frac{1}{\sqrt{NM}}[a_{t,1}(\theta_l),\ldots,a_{t,NM}(\theta_l)] \tag{4}$$

$$a_r(\phi_l)=[a_{r1}(\phi_l)] \tag{5}$$

The element(s) of the $a_t(\theta_l)$ and $a_r(\phi_l)$ are given by [13]:

$$a_{t,i}(\theta_l)=e^{-j2\pi(i-1)\frac{d_t}{\lambda}\sin(\theta_l)},\quad i=1,2,\ldots,NM \tag{6}$$

$$a_{r,i}(\phi_l)=e^{-j2\pi(i-1)\frac{d_r}{\lambda}\sin(\phi_l)}=1,\quad i=1 \tag{7}$$

where λ is the wavelength; d_t is the spacing of antennas at the BS.

The spacing of the antennas at the BS is chosen to be at least 0.5λ to enable the channel coefficients corresponding to different transmit-receive antennas to experience independent fading to enable the overall performance of the wireless system [6].

B) UE Throughput Modeling with Hybrid Beamforming

Hybrid beamforming with sub-array is used at the microwave and mmWave BS. Hybrid beamforming is more energy efficient than the fully connected architecture that utilizes N^2M phase shifters instead of the *NM* phase shifters in sub array hybrid beamforming. Also, in hybrid beamforming with sub-array, there is only one beamforming direction for all sub-antennas connected to each RF chain. This makes phase shifters in the analog beamformers to be digitally controlled and to quantize AoDs of the rays from each sub-antenna. Therefore, from the *M* antennas uniform linear array (ULA), beamforming angles are selected from the steering vectors which are given [15] as:

$$a_{ULA}(\theta)=\left[1,\ e^{j\frac{2\pi d}{\lambda}m\sin\theta},\ \ldots,\ e^{j\frac{2\pi d}{\lambda}(M-1)\sin\theta}\right]^T \tag{8}$$

Where *m* is the antenna element index with $0\le m\le M-1$

The transmit analog beamforming matrix *A* is:

$$\begin{matrix} \frac{1}{\sqrt{M}}a_t(\theta_{1,1}) & 0 & \cdots & 0 \\ 0 & \frac{1}{\sqrt{M}}a_t(\theta_{2,1}) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{\sqrt{M}}a_t(\theta_{N,1}) \end{matrix} \tag{9}$$

The AoD of each ray from different RF chains $\theta_{N,1}$ takes a uniform angle in between $[0:\frac{2\pi}{N}:2\pi)$.

Consequently, to avoid large channel matrix directly, the channel is modeled as the path in between each k^{th} UE and the n^{th} sub-array. The channel vector of the k^{th} UE is therefore given [16] as:

$$h_k^{'} = \left[h^{'}_{k,1}, \quad h^{'}_{k,2}, \quad . \quad . \quad ., \quad h^{'}_{k,N}\right] \tag{10}$$

where $h^{'}_{k,N}$ is the channel of the k^{th} UE from the n^{th} sub-array.

The channels between one UE and different sub-arrays have the AoD and path gain steering to the same transmit beamforming direction at different sub-arrays only results in a different phase for the received signals, which can be inverted by digital beamforming at the baseband [16]. The equivalent channel $\hat{H}$ at the baseband with the analog beamforming is given as:

$$\hat{H} = \left[\hat{h}_1, \quad \hat{h}_2, \quad . \quad . \quad ., \quad \hat{h}_k\right]^T \tag{11}$$

where

$$\hat{h}_k^{\,T} = h_k^{'} A \tag{12}$$

Equation (12) implies that the effective channel vector is $N \times 1$, instead of the channel information of each antenna element that corresponds to a channel vector of size $NM \times 1$. This results in a reduction of computational complexity since the number of RF chains N is much smaller than the number of antenna elements NM.

Now, given the designed analog beamforming, the digital beamforming is designed for interference cancellation among different UEs. From the effective channel $\hat{\boldsymbol{H}}$, the digital beamformer is designed by adopting the MMSE precoder, which can be implemented by:

$$D = [d_1, \quad d_2, \quad . \quad . \quad ., \quad d_k] = \hat{H}^{*} (\hat{H}\hat{H} + \alpha I^{*})^{-1} \Delta \tag{13}$$

$$D = \hat{D} \Delta \tag{14}$$

where

$$\hat{D} = \left[\hat{d}_1 \quad \hat{d}_2 \quad . \quad . \quad . \quad \hat{d}_k\right] = \hat{H}^{*} (\hat{H} H + \alpha I^{*})^{-1} \tag{15}$$

And Δ is a diagonal matrix that regulates the digital beamforming power such that the following relationship is achieved:

$$\left\| A d_k \right\|^2 = 1 \quad \forall \quad k \in K \tag{16}$$

The k^{th} diagonal element of Δ is given by:

$$\Delta_{k,k} = \frac{1}{\left\| A\hat{d}_k \right\|} \quad (17)$$

The designed hybrid beamforming has lower complexity; and it avoids the processing of large channel matrix resulting from each antenna. The achievable rate of the k^{th} UE with hybrid beamforming is derived from Shannon's capacity formula [16] as:

$$R_{i,k} = w_{i,k} \log_2\left(1 + \frac{p_{i,k}}{\sigma^2}\left|\Delta_{k,k}{}^2\right|\right) \quad (18)$$

where $w_{i,k}$ is the bandwidth allocated by the i^{th} BS to the k^{th} UK.
Substituting (17) into (18) gives:

$$R_{i,k} = w_{i,k} \log_2\left(1 + \frac{p_{i,k}}{\sigma^2\left\| A\hat{d}_k \right\|^2}\right) \quad (19)$$

Now, let

$$\beta_k = \frac{1}{\sigma^2\left\| A\hat{d}_k \right\|^2} \quad (20)$$

Therefore, equation (19) becomes:

$$R_{i,k} = w_{i,k} \log_2\left(1 + \beta_k p_{i,k}\right) \quad (21)$$

This means that the received SINR of the k^{th} UE from the i^{th} BS is given as:

$$\gamma_{i,k} = \beta_k p_{i,k} \quad (22)$$

Equation (14) gives the achievable rate of the k^{th} UE from the i^{th} BS using hybrid beamforming.

C) Energy Efficiency Modeling with Hybrid Beamforming

The energy efficiency of the i^{th} BS is the ratio of the BS sum rate and the total power consumption of the BS. The power consumption of the network is the summation of the individual power consumed by the macro, pico, and femto BSs in the HetNet. A realistic model for the total power consumption of the i^{th} BS utilizing hybrid beamforming with sub-array is a function of static power and dynamic power which depends on the power received by the UE located at a distance d from the BS. The power consumption of the i^{th} BS is, therefore, given as:

$$p_i = p_{ci} + p_{di} \quad (23)$$

where p_{ci} is the static power consumption of the i^{th} BS; p_{di} is the dynamic power consumption of the i^{th} BS

p_{ci} is made up of the baseband processing power, radio frequency chain power, and phase shifters power consumption. p_{di} is the dynamic power consumption of i^{th} BS which is from the power consumption of the power amplifier. It is given as:

$$p_{di} = \frac{1}{\eta}\sum_{k=1}^{K} x_{i,k} p_{i,k} \tag{24}$$

where $\boldsymbol{x_{i,k}}$ is the user association indicator, which is given as:

$$x_{i,k} = \begin{cases} 1, & if\ UE\ k\ is\ associated\ with\ BS\ i \\ 0, & otherwise \end{cases} \tag{25}$$

And $p_{i,k}$ is the power received by the k^{th} UE located at distance d from the i^{th} BS. It is given by the Friis space equation as:

$$p_{i,k} = p_{ti} - \rho(d) \tag{26}$$

where $\boldsymbol{p_{ti}}$ is the transmission power of the i^{th} BS; and $\rho(d)$ is the path loss of the k^{th} UE from
the i^{th} BS.
The energy efficiency of the network is, therefore, modeled as:

$$\xi = \frac{\sum_{i=1}^{B} \sum_{k=1}^{K} x_{i,k}(w_{i,k} \log_2(1+\beta_k p_{i,k}))}{\sum_{i=1}^{B} (pci + \frac{1}{\eta}\sum_{k=1}^{K} x_{i,k} p_{i,k})} \tag{27}$$

Where B is the total number of BSs deployed in the network. It consists of the number of macro BS (M_N) and the number of pico BS (P_N) and femto BS (F_N) undelayed with a macro BS. Thus, the total number of BSs deployed in the HetNet is given as:

$$B = M_N(P_N F_N) + M_N \tag{28}$$

D) Problem Formulation

Let U be the set of all UEs, $\boldsymbol{B_m}$ be the set of macrocell BSs, $\boldsymbol{B_{mm}}$ the set of mmWave picocell and femtocell BSs. When a k^{th} UE belonging to the set of all UEs (that is $\boldsymbol{k} \in \boldsymbol{U}$) is associated with an i^{th} BS (that is, $\boldsymbol{i} \in (\boldsymbol{B_m}, \boldsymbol{B_{mm}})$), the user association indicator $x_{i,k}$ is given by equation (25). A k^{th} UE connecting to an i^{th} BS gets a portion $\beta_{i,k}$ of the overall bandwidth of the i^{th} BS. Let $\boldsymbol{X} = [\boldsymbol{x_{i,k}}]_{\forall \boldsymbol{i,k}}$, $\boldsymbol{I} = \lfloor \beta_{i,k} \rfloor_{\forall i,k}$ and $\boldsymbol{P} = [\boldsymbol{p_{i,k}}]_{\forall \boldsymbol{i,k}}$ represent the matrix of user association, bandwidth allocation index, and received powers for UEs, respectively; and let $\boldsymbol{L} = [\boldsymbol{l_i}]_{\forall i}$ represent the vector of the total number of UEs connected to each BSi, where:

$$\boldsymbol{l_i} = \sum_{k=1}^{K} \boldsymbol{x_{i,k}} \tag{29}$$

The maximization of the sum energy efficiency of a system results in extremely unfair throughput allocation. To guarantee UE throughput and fairness, the energy efficiency proportional fairness criterion and the logarithmic energy efficiency utilize of the i^{th} BS when the k^{th} UE is associated with it given by [17]:

$$\xi_{i,k} = \log\left(\frac{R_{i,k}}{p_i}\right) \tag{30}$$

The logarithm function is used to form the utility energy efficiency function because it is concave and has diminishing return which encourages load balancing and fairness. The proportional fair allocation with the one that maximizes the sum of the logarithms can be identified [10]. Considering the logarithm energy efficiency utility and defined as $\Phi_i = \{k \mid x_{i,k} = 1\}$, the joint optimization problem is to find the optimal user association matrix $\boldsymbol{X}$ and bandwidth allocation matrix $\boldsymbol{I}$ that maximize the total network energy efficiency utility which is given by:

$$f(X,I) = \max_{X,\,I,\,P} \sum_{k\in K}\sum_{i\in B} x_{i,k} \log\left(\frac{\beta_{i,k}R_{i,k}}{p_i}\right) \tag{31}$$

Such that the following equations are satisfied:

$$\sum_{k\in\Phi_j} \beta_{i,k} \le 1, \qquad \forall i \in B \tag{32}$$

$$\sum_{i\in B} x_{i,k} = 1, \qquad \forall k \in K \tag{33}$$

$$\sum_{K\in K} x_{i,k} = l_i, \qquad \forall i \in B \tag{34}$$

$$\sum_{k\in K} x_{i,k} p_{i,k} \le p_{\max}, \qquad \forall i \in B \tag{35}$$

$$\sum_{i\in B} x_{i,k} R_{i,k} \ge R_{\min}, \qquad \forall k \in K \tag{36}$$

$$x_{i,k} \in \{0,1\} \qquad \forall i \in B,\ \forall k \in K \tag{37}$$

where $p_{\max}$ is the maximum transmit power of each BS; $R_{\min}$ is the minimum data rate that guarantees the QoS received by each UE. The joint user association with optimal bandwidth allocation problem is obtained as:

$$f(X) = \max_{X} \sum_{k\in K}\sum_{i\in B} x_{i,k} \log\left(\frac{R_{i,k}}{l_i p_i}\right) \tag{38}$$

The optimization problem of (38) is subjected to the constraints of (33) to (37) because the variable $x_{i,k}$ is considered.

The problem of (38) subjected to the constraints from (33)-(37) is a mixed-integer non-linear optimization problem which lacks convexity due to the objective function of logarithmic utility and the user association indicator binary nature. This makes the problem NP-hard. To solve the problem, the user association indicator is relaxed as $\boldsymbol{x_{i,k}} \in [\boldsymbol{0}, \boldsymbol{1}]$; and the Lagrangian dual analysis of the problem is presented with the view to making the problem convex. The Lagrangian L, which is associated with the optimization problem is given as [18]:

$$\begin{aligned} L(X, \mu, \lambda, \nu) = &\sum_{k\in K}\sum_{i\in B} x_{i,k} \log\left(\frac{R_{i,k}}{l_i p_i}\right) + \sum_{i\in B} \mu_i \left(\sum_{k\in K} x_{i,k} - l_i\right) \\ &- \sum_{i\in B} \lambda_i \left(p_{\max} - \sum_{k\in K} p_{i,k}\right) - \sum_{k\in K} \nu_k \left(\sum_{i\in B} x_{i,k} R_{i,k} - R_{\min}\right) \end{aligned} \tag{39}$$

where, $\mu = [\mu_1, \mu_2, \ldots, \mu_B]^T$, $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_B]^T$ and $\nu = [\nu_1, \nu_2, \ldots, \nu_K]^T$ are the Lagrange multipliers used to relax the coupled constraints.

The dual problem of the optimization problem with respect to the dual variables is written as:

$$\min_{\mu,\lambda,\nu} g(\mu, \lambda, \nu) = \begin{cases} \max\limits_{X,\, I,\, P} L(X, \mu, \lambda, \nu) \\ \quad s.t. \\ \sum\limits_{i\in B} x_{i,k} = 1, \quad \forall k \in K \\ 0 \le x_{i,k} \le 1, \quad \forall i \in B, \forall k \in K \\ \mu, \lambda, \nu \ge 0 \end{cases} \tag{40}$$

The Lagrangian dual method is used to divide the dual problem into two as follows:

$$\min_{\mu,\, \lambda,\, \nu} g(\mu, \lambda, \nu) = f_X(\mu, \lambda, \nu) + h_L(\mu, \lambda, \nu) \tag{41}$$

where:

$$f_X(\mu, \lambda, \nu) = \begin{cases} \max\limits_{X,\, P}\left(\sum\limits_{k\in K}\sum\limits_{i\in B} x_{i,k} \log(r_{i,k}) - \sum\limits_{k\in K}\sum\limits_{i\in B} x_{i,k}\left(\mu_i - \lambda_i p_{i,k} + \nu_k R_{i,k}\right)\right) \\ \quad s.t. \\ \sum\limits_{i\in B} x_{i,k} = 1, \quad \forall k \in K \\ 0 \le x_{i,k} \le 1, \quad \forall i \in B, \forall k \in K \end{cases} \tag{42}$$

and

$$h_L(\mu, \lambda, \nu) = \begin{cases} \max\limits_{L,\,P} \sum\limits_{i \in B} \left(\mu_i l_i - \lambda_i p_{\max} + \sum\limits_{k \in K} \nu_k R_{\min} \right) - \sum\limits_{i \in B} l_i \log(l_i p_i) \\ \quad s.t. \\ l_i \geq 0, \qquad \forall k \in K \end{cases} \tag{43}$$

The optimal user association matrix is the one that maximizes (38); and it is gotten by the partial derivative of (42) with respect to $x_{i,k}$, which is given as:

$$\frac{\partial f_X(\mu, \lambda, \nu)}{\partial x_{i,k}} = \log(r_{i,k}) - \mu_i + \lambda_i p_{i,k} - \nu_k R_{i,k} \tag{44}$$

Therefore, the maximizer $[\boldsymbol{x}_{i,k}]$ of $\boldsymbol{f}_{X,P}(\mu, \lambda, \nu)$ is:

$$x_{i,k} = \begin{cases} 1, & \forall\ i = i^* \\ 0, & \forall\ i \neq i^* \end{cases} \tag{45}$$

where:

$$i^* = \arg\max_i \left(\log(r_{i,k}) - \mu_i + \lambda_i p_{i,k} - \nu_k R_{i,k} \right) \tag{46}$$

Equation (46) is the judgment criterion for UE to determine the BS providing the best service. Similarly, since the function $h_L = (\mu, \lambda, \nu)$ is a differentiable function of $\boldsymbol{l_i}$, the partial differentiation of (43) with respect to l_i is given as:

$$\frac{\partial h_{L,P}(\mu, \lambda, \nu)}{\partial l_i} = \mu_i - \log(l_i p_i) - 1 \tag{47}$$

The optimal primal variables, with respect to l_i for maximizing the Lagrangian, are obtained when $\partial h_{L,P}(\mu, \lambda, \nu)/\partial l_i = 0$ and has a value of:

$$l_i^* = \frac{e^{\mu - 1}}{p_i} \tag{48}$$

By solving the dual problem of (40), a closed form expression for the optimal solution cannot be obtained directly. This is because of the second derivative of the dual function $g(\mu, \lambda, \nu)$ with respect to μ_i, λ_i, and ν_k which are all less than zero. Therefore, the subgradient method is employed to update the Lagrangian variables as follows [19]:

$$\mu_i(t+1) = \mu_i(t) - \delta(t)\left(l_i(t) - \sum_{k \in K} x_{i,k}(t) \right), \qquad \forall\ i \in B \tag{49}$$

$$\lambda_i(t+1) = \lambda_i(t) - \delta(t)\left(p_{\max} - \sum_{k \in K} x_{i,k}(t) p_{i,k}(t) \right), \qquad \forall\ i \in B \tag{50}$$

$$v_k(t+1)=v_k(t)-\delta(t)\left(\sum_{i\in B} x_{i,k}(t)R_{i,k}(t)-R_{\min}\right), \quad \forall\ k\in K \tag{51}$$

Where t represents the iteration index; and $\delta(t)$ is the step size.
By updating the Lagrange multipliers $\mu_i(t)$, $\lambda_i(t)$, and $v_k(t)$ using the respective (49), (50) and (51), $x_{i,k}(t)$ is updated accordingly using (45) and (46). This enables the dual problem to converge to the global optimum since it is convex.

E) Development of the Joint User Association Algorithm with Optimal Bandwidth Allocation

The joint user association and bandwidth allocation algorithm find the optimal user association matrix $[x_{i,k}]$ that uses the optimal bandwidth allocation. Each UE in the network measures the received power, $p_{i,k}$, from the corresponding associated BS. This necessitates the initialization of the Lagrangian parameters (μ_i, λ_i and v_k), constant step size $\delta(t)$, and a maximum number of iteration $t_{\max}$. These values are updated to converge using the sub-gradient method. Fig. 1 shows the flow chart for the implementation of the proposed algorithm.

F) Simulation Setup

The performance of the proposed algorithm was evaluated by simulation. Firstly, the minimum number of macro BS (one) which can be deployed in a HetNet, is considered. A typical urban macrocell has a radius of two km and can be deployed within a geographical area of 4 km by 4 km. The macrocell is under-lay with picocells and femtocells to form a three-tier HetNet. The cell radius of the picocells and femtocells are 0.1 km and 0.01 km as specified by [20]. The standard parameters used for the simulation are shown in Table 1. They are consistent with the simulation scenario used in a system level simulator for 5G mobile networks [21].

TABLE 1
STANDARD SIMULATION PARAMETERS

Parameters	Values
Macro BS bandwidth	20 MHz
Macro BS frequency	2 GHz
mmWave BS bandwidth	5 GHz
mmWave BS frequency	38 GHz
Macro BS transmit power	20 W
Pico BS transmit power	1 W
Femto BS transmit power	0.1 W
Noise power density	-174 dBn/Hz
Minimum UE data rate	1 Gbps

The circuitry power of different BS is also simulated as shown in Table 2 [15].

TABLE 2
CIRCUITRY POWER OF DIFFERENT BSS COMPONENTS

BS Type	Baseband Power, W	Radio Frequency Chain Power, W	Phase Shifter Power, W	Power Amplifier Efficiency
Macro BS	100	5	1	0.7855
Pico BS	0.5	0.25	0.05	0.85
Femto BS	0.2	0.12	0.02	0.90

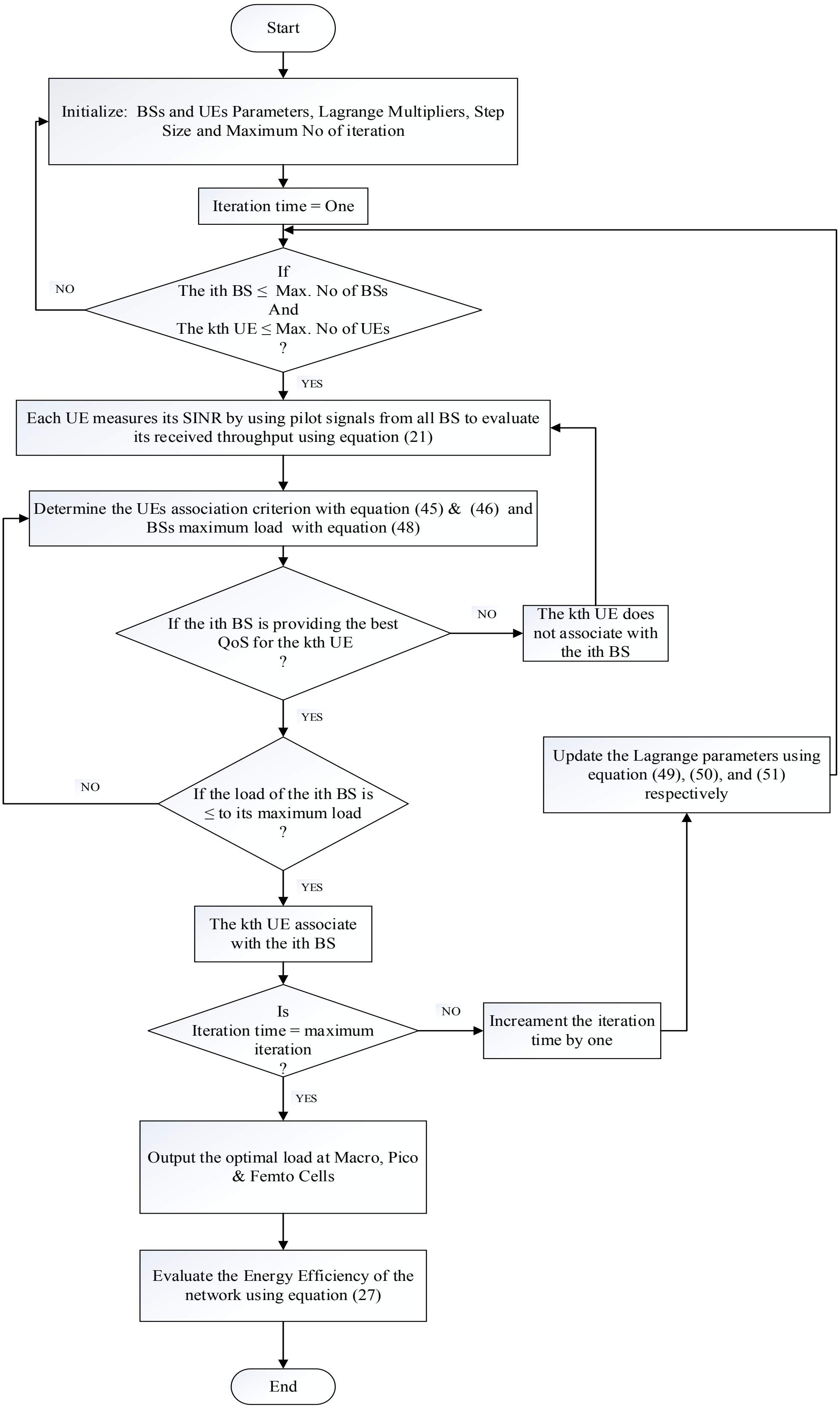

Fig. 1. Proposed user association algorithm with optimal bandwidth allocation

III. Results and Discussion

The performance of the developed user association algorithm with optimal bandwidth allocation in term of energy efficiency was compared to the existing user association algorithm. The existing user association algorithm of MaxRSRP user association algorithm and MaxSINR user association algorithm was replicated using the mathematical models given in section II (A-C) for 5G HetNets integrating massive MIMO and mmWave. The comparison with the MaxRSRP user association algorithm and MaxSINR user association algorithm was made for increasing the number of antennas, pico BSs, and femto BSs per macrocells respectively. For the energy efficiency comparison of the developed algorithm with the existing user association with increasing number of antennas per macro BS, the number of pico and femtocells per macrocell was set as 2 and 20, respectively. Also, the number of massive MIMO antennas of pico BS and Femto BS was 400 while the other simulation parameters remain the same as given in Table 1 and 2. The results are obtained for the energy efficiency of the network with a varying number of massive MIMO antennas at the macro BS for the user association algorithm with optimal bandwidth allocation, MaxRSRP user association, and MaxSINR user association as shown in Fig. 2.

Fig. 2 demonstrates the energy efficiency versus a number of massive MIMO antennas of macro BS. It is observed that regardless of the number of antennas, the user association algorithm with optimal bandwidth allocation achieves better energy efficiency than the MaxRSRP and MaxSINR user association. The develop user association algorithm with optimal bandwidth allocation (OBA) maximizes network energy efficiency through coordinating the fairness between the system load and UE's minimum data rate. For both algorithms, energy efficiency decreases with an increasing number of macro BS antennas due to increasing the power consumption of the network. The average energy efficiency, which is the mean value of energy efficiency for the user association algorithm with optimal bandwidth allocation, MaxRSRP user association, and MaxSINR user association, was computed as $3.6424\times10^{9}\ bit/Joule$, $3.3132\times10^{9}\ bit/Joule$ and $3.4542\times10^{9}\ bit/Joule$ respectively. Thus the user association algorithm with optimal bandwidth allocation has a performance improvement of 9.94% and 5.45% with respect to MaxRSRP user association and MaxSINR user association respectively in terms of energy efficiency of the network for an increasing number of macro BS antennas.

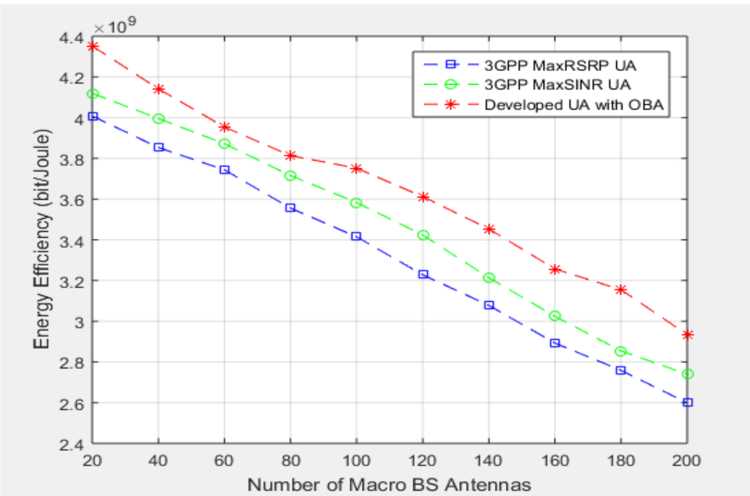

Fig. 2. Energy efficiency versus the number of massive MIMO macro BS for user association algorithms

Furthermore, the results showing the energy efficiency comparison of the proposed algorithm with the existing algorithm with an increasing number of pico BSs per macro cell are as shown in Fig. 3.

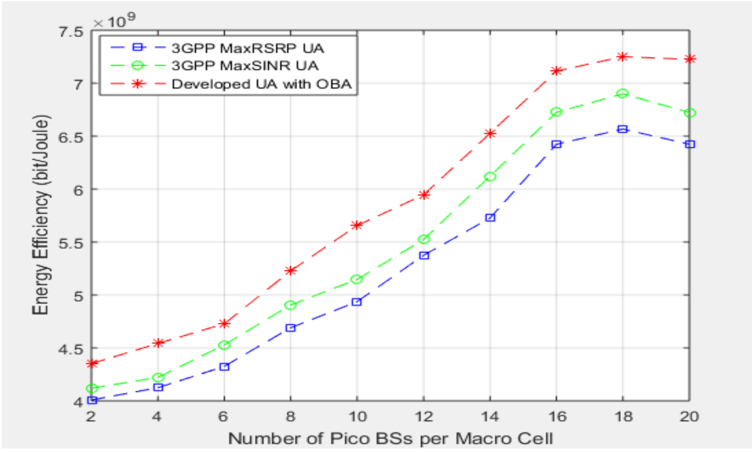

Fig. 3. Energy efficiency versus number of pico BSs per macro cell for user association algorithms

As seen from Fig. 3, energy efficiency of both algorithms increases with an increasing number of pico BSs per macrocell up to a value of 18 pico BSs per macro cell. It starts decreasing thereafter while keeping the number of antennas at the macro BS, mmWave BSs (pico BS and Femo BS) constant at a value of 20 and 400 respectively. As the number of pico BSs increases, the number of UEs associated with it also increases due to the larger bandwidth of the pico BSs. This leads to the increase sum rate of the network and subsequent increase in the energy efficiency of the network due to a decrease in the dynamic power consumption of the network. However, the increase of the energy efficiency of the network with the number of pico BSs was only up to 18 Pico BSs per macrocell, and thereafter the energy efficiency of the network began to decrease for both algorithms. Thus, the optimal energy efficiency of the network with an increasing number of pico BSs per macrocell was found at 18 pico BSs per macrocell for both algorithms. The decrease of the energy efficiency beyond this optimal value of pico BSs per macro cell is attributed to the overwhelming increase of the static power consumption of the pico BSs component which then leads to the overall reduction of the energy efficiency of the network.

The energy efficiency of the proposed algorithm outperforms the MaxRSRP user association algorithm and MaxSINR user association algorithm for the respective number of pico BSs per macro cell. The proposed algorithm associates more UEs to the pico BSs so as to guarantee the minimum UE throughput of 1 Gbps. The average energy efficiency of the proposed algorithm, MaxRSRP user association and MaxSINR user association for an increasing number of pico BSs were computed as 5.8567×10^9 bit/Joule, 5.2602×10^9 bit/Joule and 5.4916×10^9 bit/Joule respectively. For the network, the proposed user association algorithm has energy efficiency improvements of 11.33% and 6.65% over MaxRSRP user association and MaxSINR user association respectively, for an increasing number of pico BSs per macro cell.

Lastly, the results show the energy efficiency comparison of the developed user association algorithm with optimal bandwidth allocation of the existing algorithm with an increasing number of femto BSs per macro cell as shown in Fig. 4.

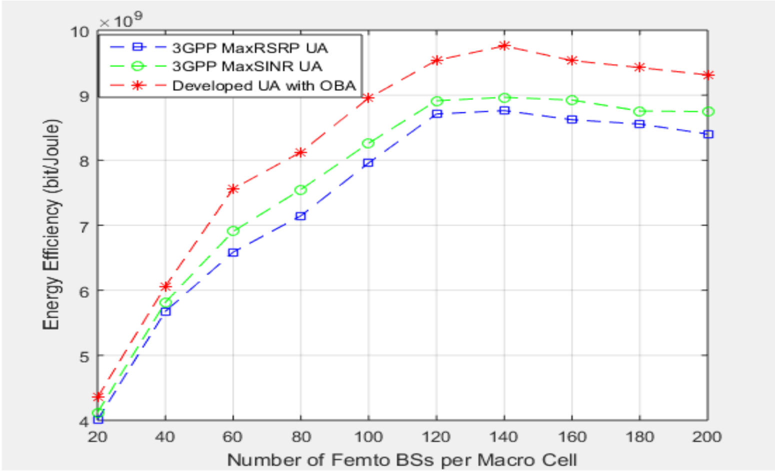

Fig. 4. Energy efficiency versus number of femto BSs per macro cell for user association algorithms

As seen from Fig. 4, the energy efficiency of both algorithms increases with an increasing number of femto BSs per macrocell up to a value of 140 femto BSs per macro cell. It starts decreasing thereafter while keeping the number of antennas at the macro BS, mmWave BSs (pico BS and Femo BS) constant at a value of 20 and 400 respectively. However, the increase of the energy efficiency of the network with the number of femto BSs was only up to 140 femto BSs per macrocell as can be seen from Fig. 4; and thereafter the energy efficiency of the network began to decrease. Thus, the optimal energy efficiency of the network with an increasing number of femto BSs per macrocell was found at 140 femto BSs per macro cell. The decrease of the energy efficiency beyond this optimal value of femto BSs per macro cell is attributed to the overwhelming increase of the static power consumption of the femto BSs component, which then leads to the overall reduction of energy efficiency of the network. The energy efficiency of the proposed algorithm outperforms the MaxRSRP user association algorithm and MaxSINR user association algorithm for the respective number of femto BSs per macro cell. The proposed algorithm associates more UEs to the femto BSs so as to guarantee the minimum UE throughput of 1 Gbps. The average energy efficiency of the developed user association algorithm with optimal bandwidth allocation, MaxRSRP user association and MaxSINR user association for an increasing number of femto BSs was computed as 8.2619×10^{9} bit/Joule, 7.4430×10^{9} bit/Joule and 7.6964×10^{9} bit/Joule respectively. For the network, the user association algorithm with optimal bandwidth allocation has energy efficiency improvements of 11.00% and 7.35% for MaxRSRP user association and MaxSINR user association respectively for an increasing number of pico BSs per macro cell.

IV. CONCLUSION

The paper presents the development of an iterative user association algorithm with optimal bandwidth allocation for energy efficiency optimization for 5G HetNet integrating massive MIMO and mmWave with hybrid beamforming. The proposed algorithm solved an energy efficiency maximization problem with respect to multiple constraints of user scheduling, load balancing, BS transmit power, and UE throughput. The user association algorithm with optimal bandwidth allocation assigns active UE's to the BS's to maximize the system energy efficiency and guarantee a minimum UE's throughput of 1Gbps. The performance of the proposed algorithm outperforms the existing MaxRSRP user association and MaxSINR user association in terms of network energy with an increasing number of massive MIMO antennas, pico BSs, and femto BSs per macro cell. The results show that the user association algorithm with optimal bandwidth allocation has network energy efficiency performance improvement of 9.94% and 5.45%, 11.33% and 6.65%, and 11.00% and 7.35% with respect to MaxRSRP user association and MaxSINR user association for an increasing number of macro BSs antennas, pico BSs, and femto BSs per macrocell respectively.

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