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Energy Efficient Resource Allocation in D2D-Assisted Heterogeneous Networks with Relays

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ABSTRACT Heterogeneous networks (HetNets) supported with relays and device to device communication can be considered as a promising solution to realize the ambitious targets of the future fifth generation networks in terms of energy efficiency and capacity. HetNets necessitate optimal power allocation, spectrum resource allocation, and cell selection to meet the quality of service requirements. In this paper, we formulate energy efficiency maximization problem in terms of resource allocation and cell selection for HetNets, where objective is to maximize the network throughput per unit network power consumption. Formulated optimization problem is non-linear fractional programming problem. We use Charnes–Cooper transformation to convert proposed fractional programming problem into concave optimization problem. We propose outer approximation algorithm (OAA) to solve the converted concave optimization problem. The proposed algorithm is evaluated by extensive simulation work. The performance of ε-optimal solution obtained by OAA method is shown for different network parameters, such as number of users, required date rate, and capacity of network.

INDEX TERMS Energy efficiency, fractional programming, HetNets, radio resource management (RRM), D2D, relay.

I. INTRODUCTION

The foreseen increase in mobile traffic over the next coming years will lead to ever more stringent design requirements in mobile networks. This is further strengthened by technological trends in microprocessors that continue to follow Moore's law [1], increasing the available processing power on your mobile handsets, opening the door for broadband and content rich application, "enabling" the global citizen. This enabling factor in this information era was already in motion in 2012, when fourth generation mobile networks were deployed under the marketing slogan any service, anytime, on any network [2]. In practice this has been partially achieved, but there is still a need for a new disruptive networking architecture that can support tighter integration between legacy and future emerging mobile networks, and break away from the technological shackles in todays network to provide a true multimedia delivery platform on demand. To provide a step towards this vision, the research community at large is now orientating fundamental research towards 5th Generation mobile networks in a bid to provide new networking platforms that can deliver 10-100x peak rate data rate, 1000x network capacity, 10x energy efficiency, and 10-30x lower latency paving the way towards Gigabit wireless [3]. These ambitious requirements of 5G mobile networks can be realized by combining gains from emerging technologies like, massive multiple input multiple output (MIMO) [4], hyper densification of small cells [5], millimeter wave (mmWave) spectrum in access network [6], visible light communication (VLC) [7], local caching [8] and green communication [9].

Share of mobile networks to global energy consumption is increasing rapidly [10], [11]. Information communication technology (ICT), which includes mobile networks, consume almost 3% of world's total energy [12], which is growing explosively. Energy consumption is directly related to carbon emissions causing greenhouse effect. Increase in energy consumption also means increase in operational expenditure (OPEX) of network. Access network consume almost 70% to 80% of total energy consumed by cellular network [13], remaining energy is consumed by core network. Energy consumption in cellular network is increased with increase in number of cells required meet the ever increasing capacity demand. Moreover energy consumption of user equipment (UE) is increasing due to high data rate requirements with always connected mode. It seems 5G mobile users will look for power source to charge batteries more frequently, and hence limiting mobility. So high capacity demand, cost of energy and carbon emission are the prime concerns which are driving research in this area. These concerns have shown need for energy efficient resource allocation strategies in 5G mobile networks which can minimize energy consumption while quality of service (Qos) standards are met.

Energy efficiency (EE) is measured in number of bits transmitted per joule of energy consumed for given time period.

$$EE = \frac{R}{P_t}. \tag{1}$$

Where R is data rate in $bits/sec$ and P_t is total power consumed in watts and hence EE is in $bits/sec/watt$ or $bits/joule$. Though $bits/joule$ is most widely used metric for EE, it does not accommodate spectral efficiency (SE). SE is defined as network throughput per unit of bandwidth measured in $bits/sec/Hz$. The metric $bits/sec/Hz/watt$ is used to accommodate SE.

Two ways in which EE can be improved include, power efficient base stations in access network and network deployment strategies such as heterogeneous networks (HetNets). HetNets can be considered as a good solution to improve EE of network. HetNets consist of macro cells overlaid by small cells (such as femto cell and pico cell) and other technologies similar to small cell (such as relay nodes, D2D communication). Small cell require low transmit power as compared to macro cell as distance between transmitter and receiver is reduced [14], thus SE per unit area improved. Low transmit power will save battery of UE as well. Moreover simple circuitry of small cell require low power and no additional energy for cooling purpose. Thus HetNets can be considered as a solution to improve EE in cellular networks. To further improve EE of HetNets, many techniques have been proposed in literature which we discuss below briefly.

A. LITERATURE REVIEW

Networks are designed with respect to busy hour, which results in waste of resources in off peak hours if cell sleep strategies are not implemented. Cell sleep strategies in HetNets have been investigated in detail in literature. Sleep mode based on traffic demand is considered as promising solution in [15] and [16], where small cells with traffic below a threshold are put to sleep. In [17], authors have developed a model that considers sleep mode along-with spectrum allocation which improves EE of HetNets. In [18] and [19], sleep control methods for small cells are proposed to improve energy consumption.

Careful deployment of small cells overlaid on existing macro cell can help improve EE beside coverage and capacity gains [20]. Many network deployment strategies are proposed to minimize network energy consumption [21]–[25]. In [22], authors consider joint base station density and transmission power optimization to minimize network power consumption subject to coverage and QoS constraints. In [23], spatial distribution of traffic is exploited to enhance radius of cells in low traffic area while meeting QoS constraints, which resulted in reduced number of cells and hence lower network energy consumption. In [24], authors use tools from stochastic geometry to find optimal maco-pico density that maximizes overall EE of network. In [25], authors formulate a traffic aware BS deployment problem to optimize the total EE of network, while satisfying the UE's maximum tolerable outage probability.

Area spectral efficiency (ASE) vs area energy efficiency (AEE) tradeoff has been formulated as an optimization problem in D2D assisted HetNets in [26], authors propose an iterative algorithm to arrive at solution. Energy efficient power optimization is considered in [27] and [28]. In [27], authors use game theoretic approach to show that the state of unique equilibrium exist for energy efficient power allocation in interference limited networks. In [28], authors formulate energy efficient power optimization problem as Nash equilibrium problem for relay assisted HetNets. The authors propose a distributed solution to Nash equilibrium problem using sequential penalty approach from advance game theory. Most of the resource allocation schemes proposed in literature for EE assume channel state information (CSI) is known. However due to unplanned deployment of small cells such as femto cells in HetNets, perfect CSI may not be available. In [29] and [30], authors propose a resource allocation scheme with incomplete CSI for energy efficient resource allocation in HetNets. Authors formulated joint resource and interference management problem as a Stackelbeg game, which is solved using backward induction method.

Transmit beam-forming has been used as solution for interference mitigation in conventional cellular networks. In [31], authors consider both beamforming and power allocation in two-tier HetNets to optimize EE. Authors in [32] propose particle swarm optimization based algorithm to solve joint power allocation and UE association problem maximizing EE. In [33], cell selection, subcarrier allocation and cell on-off strategies are jointly considered to minimize energy consumption in HetNets. In [34] authors formulate a fractional programming problem to maximize EE in D2D enabled HetNets, based on optimal power allocation and mode switch (D2D or cellular). Their approach is based on Dinkelbach method and Coordinate Ascent method to solve non-convex optimization problem. In [35] authors formulate a non-convex optimization problem of energy minimization and propose an iterative algorithm to solve it. Table 1 gives the summary of literature review on EE in HetNets.

TABLE 1. Literature Review : U.A.- UE Association, D2D - Device to device, BS - Base Station.

Ref.	Technique	Category	Constraints	U.A.	Relay	D2D	Multiple BS (Macro-Small)	Solution Domain
[14]	on/off based on traffic threshold	Sleep Control	Traffic				✓	Heuristic
[15]	on/off based on traffic threshold	Sleep Control	Traffic		✓		✓	Stochastic geometry
[16]	on/off based on traffic threshold	Sleep Control	Spectrum resue factor, cell active probability				✓	Stochastic geometry theory
[17]	on/off based on traffic threshold	Sleep Control	QoS, interference				✓	Heuristic
[18]	on/off based on dual traffic threshold	Sleep Control	Required rate				✓	Stochastic theory (Markov Chain)
[19]	Optimal number of pico cells	Deployment Strategy	Macro-pico interference, macro power				✓	Optimization theory
[20]	Joint Partial Spectrum Reuse and Macro-pico density	Deployment Strategy	Min. required rate, outage probability				✓	Optimization theory
[21]	Joint macro transmit power and macro-pico density optimization	Deployment Strategy	Coverage performance	✓			✓	Optimization theory/Stochastic geometry
[22]	Cell Range Extension	Deployment Strategy	Spatial traffic distribution					Stochastic geometry
[23]	Optimal macro-pico density	Deployment Strategy	Macro-pico density				✓	Stochastic geometry
[24]	Traffic aware Optimal BS density	Deployment Strategy	Min outage probability, Min required rate					Optimization theory
[25]	Joint mode selection, subcarrier and power Allocation	Resource Allocation	EE , Transmit power			✓	✓	Optimization theory
[26]	Transmit Power Optimization	Resource Allocation	Interference					Game Theory (Nash equilibrium)
[27]	Transmit Power Optimization	Resource Allocation	Min Required Rate		✓		✓	Game Theory (Nash equilibrium)
[28]	Transmit Power Optimization	Resource Allocation	Interference				✓	Game Theory(Stackelberg equilibrium)
[29]	Transmit Power Optimization	Resource Allocation	Interference				✓	Game Theory(Stackelberg equilibrium)
[30]	Transmit beam forming and power allocation	Resource Allocation	Min. required rate				✓	Optimization theory
[31]	Joint power allocation and UE association	Resource Allocation	Cell Bias value and transmit power	✓			✓	Optimization theory
[32]	Joint cell selection and subcarrier allocation	Resource Allocation	Number of resource blocks	✓			✓	Optimization theory
[33]	Joint mode selection and power allocation	Resource Allocation	Required rate, transmit power	✓		✓	✓	Optimization theory
[34]	Joint sub-channel and power allocation	Resource Allocation	Required rate, interference	✓			✓	Optimization theory

B. CONTRIBUTIONS

Based on literature review and having a close look at Table 1, we conclude that, "Energy efficient resource allocation techniques exist in literature for macro-femto or macro-pico OFDMA HetNets, but there is no joint UE association and power allocation scheme that considers optimization of EE ($bits/sec/Hz/watt$) in D2D assisted mutil-cell HetNets supported with relays." The main contributions of proposed work are summarized below

- We give mathematical formulation for EE maximization problem in D2D assisted HetNets with relays. We consider optimal power allocation along with UE association subject to minimum data rate requirement.
- We prove that the problem in consideration is a concave fractional programming problem, which can be converted to concave optimization problem using Charnes-Cooper method.
- We use outer approximation algorithm to arrive at an ε-optimal solution.
- We provide extensive evaluation results to verify the validity of ε-optimal solution of proposed problem formulation.

Rest of the paper is organized as follows, section II gives system model and problem formulation, section III discusses the algorithm proposed to achieve near optimal solution, section IV gives experimental and numerical results.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider LTE-A HetNet, shown in Fig. 1, where UEs are served either by macro cell, small cell, relay or they are

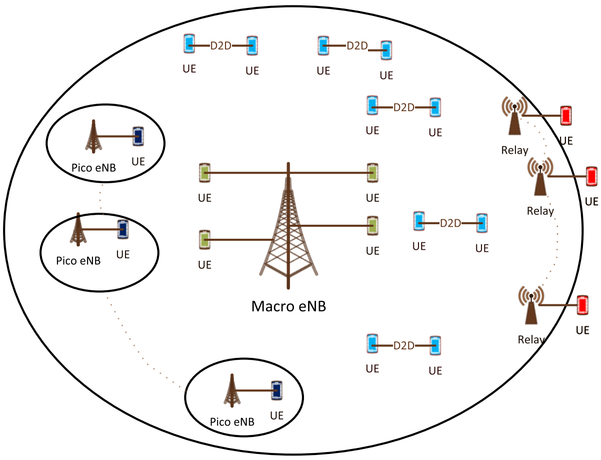

FIGURE 1. LTE-A HetNet scenario .

in D2D mode. Macro cell is covering large area to provide coverage to maximum number of UEs. Relay node (RN) will be extending coverage of its donor macro cell. Certain UEs in close proximity in macro cell coverage can use D2D mode for communication. Small cells are placed inside macro cell coverage to accommodate more UEs, i.e to increase the capacity.

Let x_i^k be the binary indicator to show UE k is connected by whom among the **m**acro cell, **s**mall cell, **r**elay and **D**2D, i.e $i \in \mathcal{M}$ and $\mathcal{M} = \{m, s, r, d\}$, where m = macro cell, s = small cell, r = relay and d = D2D . If $\mathcal{K}$ be the set of UEs that want to communicate among each other i.e $\mathcal{K} = \{1, 2, 3......K\}$, then we can write $x_i^k \in \{0, 1\} \ \forall\, i \in \mathcal{M}, k \in \mathcal{K}$.

Power received in down-link by UE k from BS i is denoted by p_i^k where $i \in \mathcal{M}$. The channel gain between k^{th} UE and BS i is h_k, G_o be the antenna gain and $\zeta 10^{\zeta/2}$ be the lognormal shadowing, where ζ is the zero mean gaussian random variable with standard deviation σ [36], and the channel gain h_k is modeled as $h_k = \bar{h}_k \zeta G_o \left(\frac{d_o}{d}\right)^{\alpha}$, where d is the distance between transmitter and receiver, d_o denotes antenna far field reference distance, α is path loss exponent, $\bar{h}_k$ is Rayleigh random variable. The channel capacity of k^{th} UE on BS i is denoted as C_i^k. A summary of symbol notation is given in Table 2.

In this paper, we formulated the problem that maximizes energy efficiency, based on power allocation and cell selection in LTE-A HetNets. Mathematically, we have

$$\max_{xp} U(x, p) = \frac{\sum_{i\in\mathcal{M}} \sum_{k\in\mathcal{K}} x_i^k c_i^k}{P_c + \sum_{k\in\mathcal{K}} p_m^k + p_s^k + p_r^k + p_d^k}$$
$$\text{subject to } C1: \sum_{i\in\mathcal{M}} x_i^k \leq 1, \forall\, k \in \mathcal{K},$$
$$C2: \sum_{i\in\mathcal{M}} \sum_{k\in\mathcal{K}} p_i^k \leq P_i,$$
$$C3: p_i^k \leq x_i^k P_i \ \forall\, i \in \mathcal{M}, k \in \mathcal{K},$$
$$C4: \sum_{i\in\mathcal{M}} x_i^k c_i \geq \sum_{i\in\mathcal{M}} x_i C^k \ \forall\, i \in \mathcal{M}, k \in \mathcal{K},$$
$$C5: p_i^k \geq 0 \ \forall\, i \in \mathcal{M}, k \in \mathcal{K}. \tag{2}$$

TABLE 2. Notations.

Symbol	Definition
K	Number of UEs
x_m^k	Binary indicator to show whether UE k is connected to macro cell or not.
x_s^k	Binary indicator to show whether UE k is connected to small cell or not
x_r^k	Binary indicator to show whether UE k is connected to Relay or not
x_d^k	Binary indicator to show whether UE k is connected in D2D pair or not
p_m^k	Power received by kth UE on macro cell
p_s^k	Power received by kth UE on small cell
p_r^k	Power received by kth UE on Relay
p_d^k	Power received by kth UE in D2D mode
P_i	Max. transmit power of BS i
d_o	Close in reference distance according to antenna far field
d	Distance between transmitter and receiver
α	Path loss exponent
h_k	Channel gain between UE and macro cell/small cell/relay/D2D pair
N_o	Additive white gaussian noise
G_o	Antenna gain
ζ	Zero mean gaussian random variable for shadowing
c_i	Capacity of BS i
C^k	Total Capacity
c_i^k	Capacity of kth UE on BS i
p_i^k	Power of kth UE on BS i
$C1 - C5$	Constraint 1 to Constraint 5

The objective of function in equation (2) is to maximize EE ($bits/sec/Hz/watt$) with serving cell selection subject to constraints $C1$ to $C5$. Constraint $C1$ is BS selection constraint that any UE will be severed by one of BS (macro cell, small cell, relay or D2D). Constraint $C2$ is maximum power constraint for macro cell, small cell, relay and D2D. Constraint in $C3$ ensures that power experienced by any UE must be zero if it is not connected to concerned BS. Constraint $C4$ ensures minimum rate of each UE must be greater than required rate. Constraint $C5$ ensures minimum power of each UE.

A. ALTERNATE FORMULATION

The problem in equation (2) is concave fractional programming problem (CFP) as numerator is a concave function and denominator is a convex function, where c_i^k and p_i^k are real valued functions defined on subset of R^n. We can apply Charnes-Cooper transformation (CCT) to CFP of equation (2) to convert it into a concave programme, where $p = \left(\frac{y}{t}\right)$. See the Appendix for transformation of CFP to a concave programme using CCT.

The equivalent concave problem can be written as follows

$$\max_{yt} U(y, t) = t \sum_{i\in\mathcal{M}} \sum_{k\in\mathcal{K}} x_i^k log\left(1 + \frac{y_i^k h_k}{tN_o}\right)$$
$$\text{subject to } C1: \sum_{i\in\mathcal{M}} x_i^k \leq 1, \ \forall\, k \in \mathcal{K},$$
$$C2: \sum_{i\in\mathcal{M}} \sum_{k\in\mathcal{K}} y_i^k - P_i t \leq 0,$$
$$C3: y_i^k - x_i^k t P_i \leq 0 \ \forall\, i \in \mathcal{M}, k \in \mathcal{K},$$

$$C4: \sum_{i\in\mathcal{M}} x_i^k log\left(1+\frac{y_i^k h_k}{tN_o}\right) \geq \sum_{i\in\mathcal{M}} x_i C^k \; \forall\, i \in \mathcal{M}, k \in \mathcal{K},$$
$$C5: y_i^k \geq 0 \; \forall\, i \in \mathcal{M}, k \in \mathcal{K},$$
$$C6: P_c t + \sum_{i\in\mathcal{M}} \sum_{k\in\mathcal{K}} y_i^k = 1. \qquad (3)$$

The problem in equation (3) is is mixed integer nonlinear optimization problem. These kind of problems are NP-hard in nature. There is no algorithm that can give optimal solution with increase in the number of discrete variables in polynomial time. We have continuous variables y_i as well as binary variables x_i . Search space of (3) increases exponentially with the number of UEs (K). One way to get near optimal solution is to perform exhaustive search on binary variable and for known binary value, apply the convex optimization. For exhaustive search, the search space for binary variable is $2^{|K|}$, i.e we need to solve $2^{|K|}$ optimization problems. Due to complexity of exhaustive search, in this paper, we propose OAA [37], which give near optimal solution with guaranteed convergence. The OAA iteratively reduce the duality gap between master and primal algorithm. In the next section, we will give detail implementation of OAA for energy efficient cell selection and power allocation.

III. PROPOSED APPROACH

The combination of integer and continuous variables along with their non-linear behaviour makes the problem in equation (3) very complex and challenging. However, by exploiting special structure of the problem, we can use OAA as a solution to this problem. OAA gives ε-optimal values of y_i and t , using these values in equation (2), we get ε-optimal values for energy efficiency. The algorithm is shown in Fig. 2.

A. DESCRIPTION OF ALGORITHM

Let $\mathcal{U}$ be objective function and ϕ_{c1-c6} be constraints $C1$ to $C6$ in equation (3), $Y = \{y_m, y_s, y_r, y_d\}$ and $X = x \cup Y$. It can be proved that, for equation (3), Y is convex, non-empty and compact. The constraint function ϕ_{c1-c6} as well as objective function $\mathcal{U}$ is convex in Y. Both ϕ_{c1-c6} and $\mathcal{U}$ are differentiable once, for fix values of Y. By fixing X, we can get non linear programming problem (NLP), which can be solved.

The OAA will converge with convergence capability ε in finite number of iterations [38]. The OAA follows lower bounds which do not decrease and upper bounds which do not increase. The sequence of upper bounds (Upper_bound) is found by solving primal-subproblem, whereas sequence of lower bounds (Lower_bound) is found by solving corresponding master problem. The problem in (3) is divided into primal problem and master problem to find a sequence of lower and upper bounds. Fixing X variables gives primal problem. At the kth iteration of OAA, let us suppose integer variable have the value X^k. The primal-problem is described as

$$\min_{Y} -\mathcal{U}\left(X^k, Y\right)$$
$$\text{subject to: } \phi_{c1-c6}\left(X^k, Y\right) \leq 0. \qquad (4)$$

By solving problem in (4) we get Y^k and use it for master-problem. By solving primal-problem, we get upper bounds, and by solving master-problem, we get lower bounds. The primal solution i.e Y^k helps to drive master problem. Master-problem is derived around the solution to primal problem Y^k, by applying outer approximation on objective function $\mathcal{U}$ and constraint function ϕ_{c1-c6}, i.e by making the objective function $\mathcal{U}$ and constraint function ϕ_{c1-c6} linear [39] [40]. By solving master problem, we get integer variables X^{k+1} to be used in next iteration. After each iteration in algorithm, lower bound and upper bound get close to each other , and algorithm terminates when difference between the upper bound and lower bound is less than ε . We can rewrite the problem in (3)

$$\min_{X} \min_{Y} -\mathcal{U}\left(X^k, Y\right)$$
$$\text{subject to: } \phi_{c1-c6}\left(X^k, Y\right) \leq 0. \qquad (5)$$

We can also write (5) as

$$\min_{X} - \vartheta\,(X) \qquad (6)$$

where

$$\vartheta\,(X) = \min_{Y} -\mathcal{U}\left(X^k, Y\right)$$
$$\text{subject to } \phi_{c1-c6}\left(X^k, Y\right) \leq 0. \qquad (7)$$

The problem in (6) is projection of (3) on $\mathcal{X}$ space. As all constraints hold for primal problem in (4) for all $\mathcal{X}^k$, so solution to the projection problem is given below

$$\min_{X} \min_{Y} -\mathcal{U}\left(X^k, Y^k\right) - \nabla\mathcal{U}\left(X^k, Y^k\right)\begin{pmatrix} Y - Y^K \\ X - X^k \end{pmatrix}$$
$$\text{subject to } \phi_{c1-c6}\left(X^k, Y^k\right) - \nabla\phi_{c1-c6}\left(X^k, Y^k\right) \times \begin{pmatrix} Y - Y^k \\ X - X^k \end{pmatrix} \leq 0. \qquad (8)$$

We introduce a new variable η, equivalent minimization problem can be rewritten as:

$$\min_{X,Y,\eta} \eta$$
$$\text{subject to } \eta \geq -\mathcal{U}\left(X^k, Y^k\right) - \nabla\mathcal{U}\left(X^k, Y^k\right)\begin{pmatrix} Y - Y^k \\ X - X^k \end{pmatrix},$$
$$\phi_{c1-c6}\left(X^k, Y^k\right) - \nabla\phi_{c1-c6}\left(X^k, Y^k\right)\begin{pmatrix} Y - Y^k \\ X - X^k \end{pmatrix} \leq 0. \qquad (9)$$

The problem in (9) is master problem, which gives lower bounds. If Y is convex, non-empty & compact and the constraint function ϕ_{c1-c6} as well as objective function $\mathcal{U}$ is

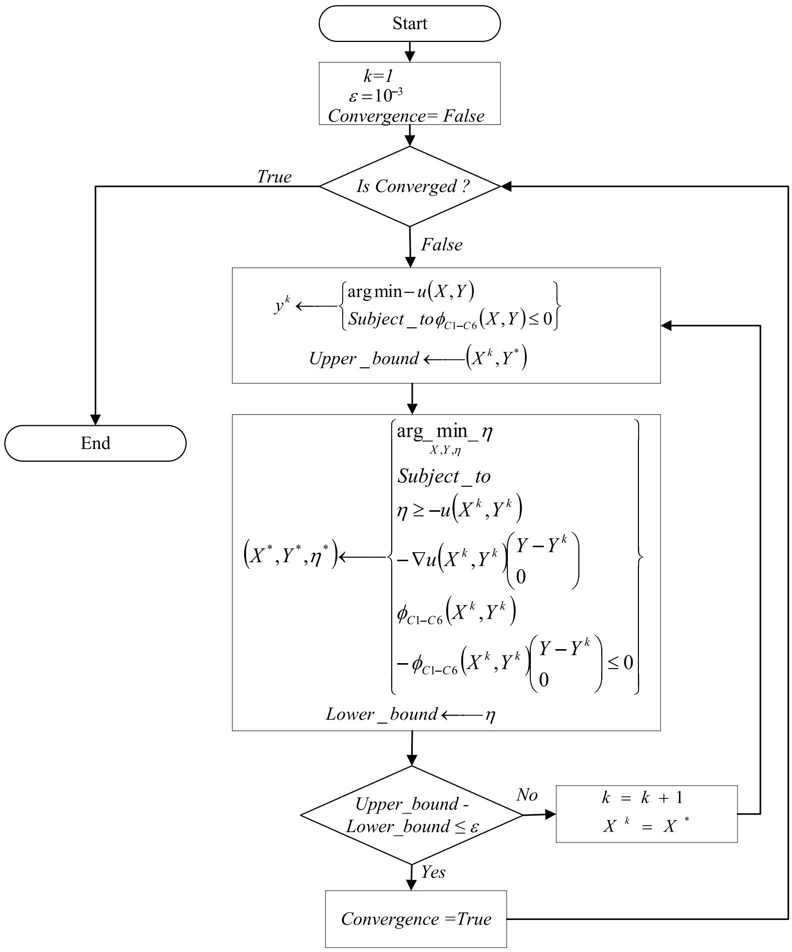

FIGURE 2. Algorithm for Outer Approximation .

convex in Y, then master-problem in (9) is equivalent to (3). Problem in (9) is mixed integer linear programming(MILP) problem, which can be solved using iterative approaches like branch and bound algorithm [41].

B. OPTIMALITY AND CONVERGENCE OF ALGORITHM

According to [37] and [39], the OAA converges linearly. Complete proof can be found in [37]. The algorithm is optimal as for fixed values of X, objective function and constraints are convex. The OAA have branch and bound architecture, which makes it optimal in $\varepsilon = 10^{-3}$ for fixed values of $\mathcal{X}$.

Algorithm will terminate in finite number of steps with $\varepsilon = 10^{-3}$ optimal solution only if objective function $\mathcal{U}$,and constraint function ϕ_{c1-c6} are convex in Y. For fixed values of Y, $\mathcal{U}$ and ϕ_{c1-c6} must be continually differentiable once. The optimality of Y in (9) states that η is greater than $\mathcal{U}\left(X^k, Y^k\right)$ for any point in (9) that is feasible. If η is less than $\mathcal{U}\left(X^k, Y^k\right)$, then no feasible solution exists for master problem for the given X. For any value of X^k in (9) if feasible solution does not exist, it will be excluded for subsequent master problems. This leads to convergence of the algorithm.

IV. EXPERIMENTAL RESULTS

Experimental results attained via our simulation setup, portray performance of proposed approach to solve fractional programming problem in equation (2) in terms of EE and throughput of network. The results also give some insight on convergence of proposed algorithm. To implement outer approximation, basic open source nonlinear mixed integer programming (BONMIN) [42] is used.

A. SIMULATION SETUP

System parameters are given in Table 3. For all the simulations, maximum radius of macro cell, small cell, relay and D2D pair is set to 1000m. The maximum power for macro cell P_m, small cell P_s, relay P_r and D2D pair P_d are set to 24, 12, 12 and 3 watts respectively. Minimum data rates required are {100,200,300,400,500,1000} Kbps. Minimum UEs allowed are 2, where as maximum UEs allowed are 30 with an increment of 2. Close in reference distance according to antenna far field d_o, is set to 10m and d is always greater than d_o. Path-loss exponent α is 2 and zero mean gaussian random variable for shadowing ζ is 10 dB. The total circuit power P_c is set to 10^{-6} watts. All the UEs, small cells, D2D

TABLE 3. System Parameters.

Parameter	Value
P_m	24 watts
P_s	12 watts
P_r	12 watts
P_d	3 watts
d_o	10 m
α	2
eNB radius	1000 m
G_o	50
ζ	10dB
C_k	{100,200,300,400,500,10000}kbps
Min UEs	2
Max UEs	30
UE Increment	2

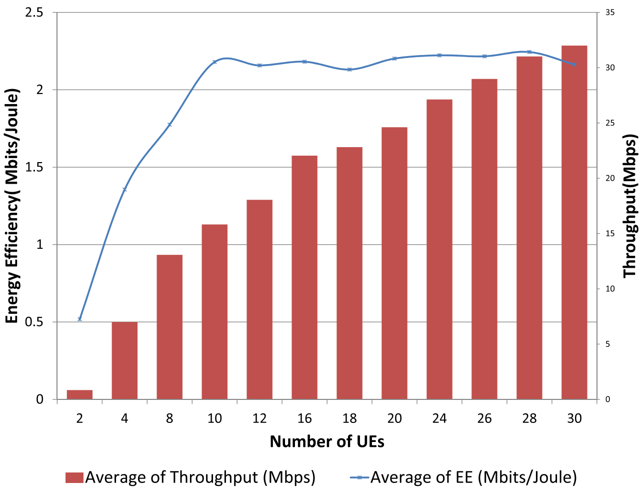

FIGURE 3. EE and throughput of HetNet vs number of UEs .

pairs and macro base stations are uniformly distributed in the network.

B. RESULTS AND DISCUSSIONS

ε-optimal energy efficient cell selection and power allocation are achieved using concave fractional programming. Fig. 3 shows EE and throughput plots with respect to number of UEs.

It is evident from the Fig. 3 both throughput (sum rate of all UEs) and EE increase with increase in number of UEs for the proposed method. If we further increase number of UEs, EE slightly decrease.

Fig. 4 depicts EE plots with respect to required data rate. Increasing required rate decreases EE, which is obvious as more power is required to maintain high data rates.

Fig. 5 presents EE plots with respect to number of UEs for required data rates 100 Kbps, 500 Kbps and 1 Mbps. For 100 kbps, as we increase number of UEs, EE is better compared to 500 kbps and 1 Mbps, which reinstates the fact that EE decreases with increase in required data rate.

Fig. 6, 7 and 8 show number UEs attached to macro cell, small cell, relay or D2D pair, under ε-optimal power allocation to gain better EE. As depicted from Fig. 6, for required rate 100 kbps, when total number of UEs are low, all type of

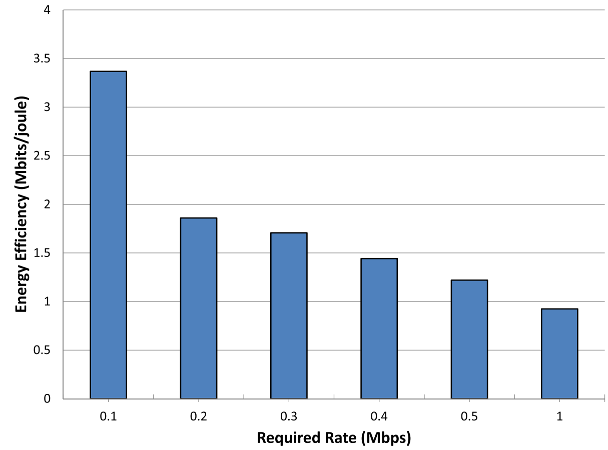

FIGURE 4. EE of HetNet vs required data rate .

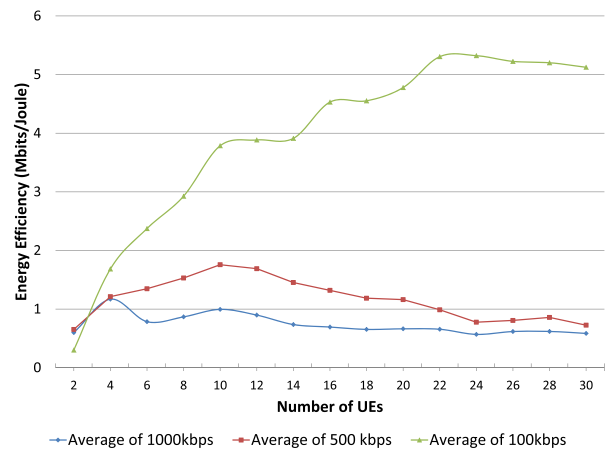

FIGURE 5. EE vs number of UEs, for various required data rates .

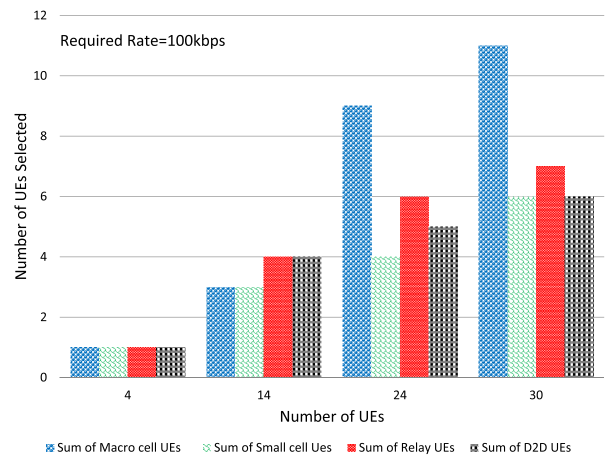

FIGURE 6. UE distribution in HetNet for required rate = 100kbps .

technologies (macro cell, small cell, relay and D2D) get equal number of UEs, but as we increase number of UEs macro cell become dominant in acquiring UEs. Similarly for 500 kbps, it is evident from Fig. 7, UE distribution is similar for low number of UEs and macro cell is getting largest number of UEs, when total number UEs are increased. However if we

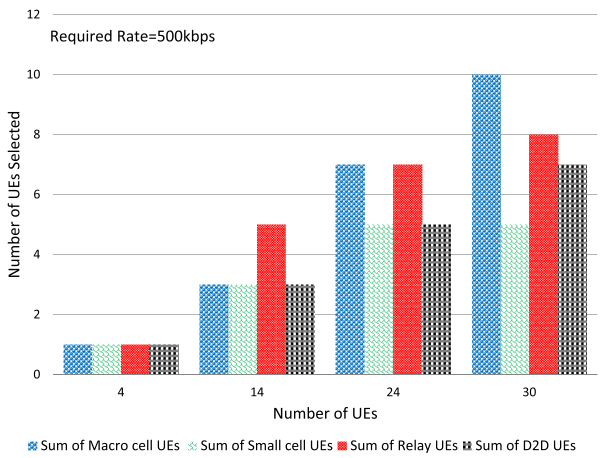

FIGURE 7. UE distribution in HetNet for required rate = 500kbps .

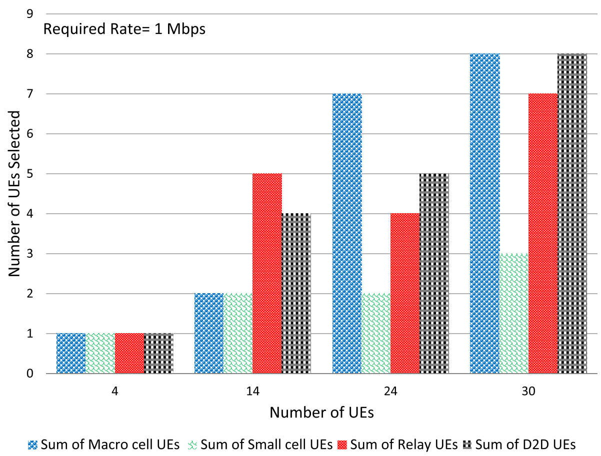

FIGURE 8. UE distribution in HetNet for required rate = 1 Mbps .

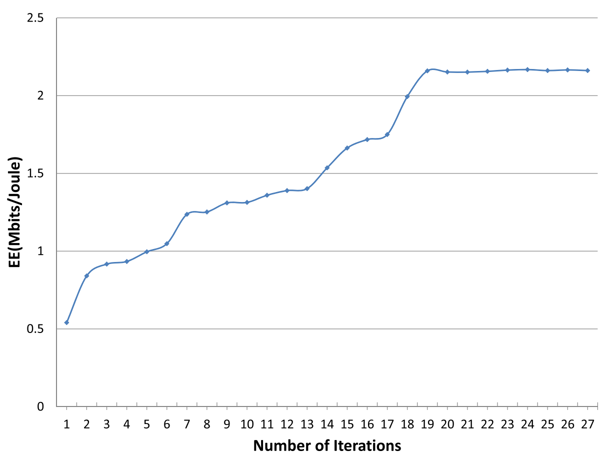

FIGURE 9. EE vs number of iterations .

increase data rate to 1 Mbps, as described in Fig. 8, for low number of UEs (such as 4 UEs) all technologies get same number of UEs, but at as we increase number of UEs, D2D becomes dominant and get more UEs. Hence for low data rates i.e 100 kbps more UEs are attached to macro cell and for high data rate i.e 1 Mbps, more UEs are engaged in D2D communication, as we increase total number of UEs.

Fig. 9 depicts EE vs number of iterations, which gives us some insight to convergence of proposed algorithm. Algorithm converges to suboptimal solution under 20 iterations.

V. CONCLUSION

In this paper, we discussed optimization problem of cell selection and power allocation that maximizes energy efficiency in $bits/sec/Hz/watt$ for LTE-A HetNets. The problem we considered is concave fractional programming problem. We converted the concave fractional programming problem to concave optimization problem using Charnes-Cooper transformation, which can be solved using standard optimization tools. We exploit special structure of problem, and suggest OAA as solution to the problem. The proposed OAA converges linearly and gives optimal results with-in $\varepsilon = 10^{-3}$. The performance of ε-optimal solution obtained by OAA method is shown for different system parameters such as number of UEs, required date rate and throughput of network. EE improve with increasing number of UEs and becomes stable if we further increase UEs. EE decreases with increase in required data rate. Increasing required data rate also results in more UEs engaged in D2D communication.

APPENDIX

FRACTIONAL PROGRAMME AND CHARNES-COOPER TRANSFORMATION

In a fractional programme (FP), objective function is ratio of two functions that are nonlinear in general. If $f(z)$, $g(z)$ and $h_k(z)$ (where $k = 1, 2...m$) defined on set $S \subset R^n$, having real values, a fractional programme is defined as

$$\begin{aligned} &\max_{z \in S} \frac{f(z)}{g(z)} \\ &\text{subject to } C1 : h_k(z) \leq 0. \end{aligned} \tag{10}$$

If g(z) is positive and convex, f(z) is positive and concave, assuming S is convex set, then FP is called concave fractional programme (CFP).

Charnes-Cooper transformation [43] use following variable transformations to reduce a CFP to a concave programme.

$$y = \frac{z}{g(z)}, \tag{11.a}$$

$$t = \frac{1}{g(z)}. \tag{11.b}$$

The equivalent concave problem for equation (10) can be written as

$$\begin{aligned} &\max_{\frac{y}{t} \in S} \; t f_0\left(\frac{y}{t}\right) \\ &\text{subject to } C1 : tg\left(\frac{y}{t}\right) = 1, \\ &\qquad C2 : th_k\left(\frac{y}{t}\right) \leq 0 \;\; \forall \;\; k = 1, 2, 3 \ldots m. \end{aligned} \tag{12}$$

Problem in equation (10) can have optimal solution if and only if problem in equation (12) have optimal solution.

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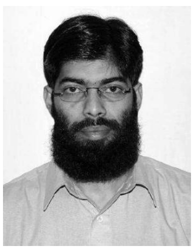

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