Energy efficiency optimization for downlink OFDMA system in heterogeneous network with QoS constraints

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SUMMARY

Energy efficiency (EE) has currently turn into one of the major issues in heterogeneous networks (HetNet) paradigm of today's wireless communication industry. In this paper, we optimize EE for downlink OFDMA system in HetNet, taking into account realistic network power consumption model, that is, considering circuit power. This paper investigates the EE maximization using convex optimization theory where primary optimization criterion is data rate in a downlink multiuser HetNet. Given QoS (data rate) requirement, for maximizing EE, a constrained based optimization problem is devised. Because the optimization problem is non-convex in nature, we reconstruct the optimization problem as a convex one and devise a pragmatically efficient novel resource assignment algorithm for maximizing achievable EE, with quick convergence. The considered optimization problem is transformed into a convex optimization problem by redefining the constraint using cubic inequality, which results in an efficient iterative resource allocation algorithm. In each iteration, the transformed problem is solved by using dual decomposition with a projected gradient method. Analytical insights and numerical results exhibit the potency of the devised scheme for the targeted complex wireless systems.

KEY WORDS: energy efficiency; green; HetNet; LTE-advanced

1. INTRODUCTION

Nowadays information and communication technology (ICT) acts as one of the major sources to increase global greenhouse gas emissions because the quantity of energy consumption for ICT has been increasing rapidly [1]. Consequently, achieving high-energy efficiency (EE) is turning out to be a prime concern for designing of the future wireless communications paradigm. Energy saving is predominantly positioning itself at the forefront of system design, as operators look to increase EE, that is, bits per Joule. This design paradigm is also synchronized with global priorities on energy management, where recently published figures suggest [2] that ICT infrastructures are responsible for 3% of the worldwide energy consumption, inducing approximately 2% CO_2 emissions worldwide [2]. In reaction towards these global trends, the 3rd Generation Partnership Project standards are currently considering new EE approaches into the design of fourth generation and beyond mobile networks across the entire protocol stack, from physical layer to networking, in unison with new networking topologies and deployment strategies. Where, once before, spectral efficiency (SE) was the performance metric of choice; now, EE and the engineering trade-off between both metrics are also scrutinized to find an appropriate trade-off.

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One of the reference scenarios are heterogeneous networks (HetNet) [3], as a system comprising a blend of larger cells (i.e., macro cells) and small cells (low-power nodes) in which some may be designed and deployed with limited access and some without wired backhaul. HetNet is a promising concept for gaining more SE and enhanced area of coverage in future wireless cellular systems. By positioning, low-power nodes associated with macro cells, small cells are created and usually utilized to broaden the area of coverage or bandwidth (e.g., through relay) where desired signals from macro station do not reach appropriately or to increase capacity of network (i.e., pico cell and femtocell) in places where high density of data usage is required. In order to have efficient interference management inside a heterogeneous network, a clear point of coordination among different kinds of nodes is needed. The coordination between the macro base station, such as evolved Node B (eNB), and small base stations, such as pico cell, or low-power nodes, such as relay transmitter, is the prime example.

1.1. Related work

Energy efficiency have been investigated for various scenarios of wireless communication networks in research literature. The foremost work where orthogonal frequency-division multiplexing (OFDM) system has been applied for EE optimization using circuit power consumption is [4]. In [5], an energy-efficient transmission rate and the transmit power adaptation scheme is proposed for the orthogonal spacetime block coding MIMO system where channel state information at the transmitter is not perfect. For single-cell orthogonal frequency-division multiple access (OFDMA) networks, EE is analyzed in [6]. The study in [7] has also targeted the similar scenario like previous work applying particle swarm optimization techniques. Furthermore in [8], the resource allocation is formulated to maximize EE for secure OFDMA systems as a mixed nonconvex and combinatorial optimization problem with negligible circuit power taking into consideration for single-cell scenario. In [9], EE in OFDM distributed antenna systems in single cell scenario is also analyzed. EE comparison of the different types of MIMO systems is also present in [10].

Current technologies that address EE resource management for cooperative and competitive HetNet systems under a variety of network objectives and constraints is not yet fully developed [11]. Although much work on EE network deployment strategies has been done, current results are still quite rudimentary, and some important challenges remain to be investigated [12]. For example, the EE optimization in HetNet for downlink OFDMA system is worth investigating. In [13], the performance of conventional HetNet in terms of EE is first introduced, although only pico-cell is considered. Moreover, a multiple radio access technology HetNet energy optimization is provided by [14], but multi-tier EE optimization is still unavailable. In [15], the design of EE cellular networks by employing of base station sleep mode strategies as well as small cells, and the trade-off issues associated with these techniques, is investigated. Furthermore, optimization problems in the form of power consumption minimization are formulated, and the optimal operating frequency of the macro cell base station is also determined. The work in [16] looks into energy efficient ways of operating dense small cell networks by applying concepts from cognitive radio. A vertical power-optimized (considering static circuit and transmit power) handover mechanism is proposed in [17] for HetNet. However, there are few studies analyzing EE optimization considering both types of circuit power (static and dynamic) in HetNet.

1.2. Contribution

This work provides more insights into the optimal EE for downlink OFDMA in a multi-tier HetNet cellular system, under essential QoS requirements, that is, radio resource constraints. In this paper, the maximization of EE as a convex optimization problem for HetNet is addressed. We consider the consumption of both transmit and circuit (static and dynamic) power in the design of optimal EE systems. The objective of the optimization problem is to maximize EE while fulfilling minimum QoS (rate) requirements. To solve this problem, we remodel the optimization problem as a convex one and then propose a novel rate optimization algorithm to achieve maximum EE, with a good convergence time. Hence, we first formulate the optimization problem where constraints are modeled as a cubic inequality [18], and then we propose a novel resource allocation algorithm to achieve

maximum EE for a given SE, which includes both transmit and circuit power for HetNet scenario. We develop an algorithm using gradient method by constructing Lagrangian function and checking that solution with Karush–Kuhn–Tucker (KKT) condition [19].

1.3. Paper organization

The rest of the paper is organized as follows. In section 2, the system model is described, and we formulate an optimization problem to maximize the EE in section 3. Section 4 provides a novel optimizing rate allocation algorithm to achieve maximum EE in HetNet. Numerical results are demonstrated and discussed in section 5. Finally, section 6 concludes the paper and identifies open problems and possible future work.

2. SYSTEM MODEL

Heterogeneous networks are networks with multiple nodes with different transmission power. For example, HetNets may comprise macro cells, pico cells, relays, and so on. In our scenario, we consider not only a conventional HetNet but also a design HetNet with interference coordination between different cells. We propose a system architecture based on LTE technology, as given in Figure 1.

One HetNet cell-site has one eNB (which is the main macro cell) and several pico cells and relays. One HetNet can be coordinated to other HetNets to coordinate inter-cell interference (ICI), therefore negligible ICI is present. We adapted the coordination techniques from [20], which is our previous work. We have to deal only with the intra-cell interference in each HetNet, caused by the unavoidable cell overlap. Each macro, pico, and relay is designed in a different frequency range as illustrated in the architecture figure by different colors. So each pico cell receives interference from other pico cells within the same HetNet cell-site. This also applies to relays. The impact of the intra-cell interference for HetNet in this scenario is negligible because the pico cells or relays are deployed at far distance, and the macro-eNB manages this interference through power control and the backhaul between the eNB and the pico or relay links [21, 22]. Therefore, there is inconsiderable amount of interference between the low-power nodes inside one HetNet cell-site to degrade the system efficiency in a drastic manner.

We take into account HetNet cell-site with downlink OFDMA network containing U active users. The aggregate bandwidth B is evenly divided into M physical resource blocks (PRB), where each PRB with a bandwidth of $W = B/M$. Let $\mathcal{U} = \{1, 2, \ldots, U\}$ and $\mathcal{M} = \{1, 2, \ldots, M\}$ define the sets of
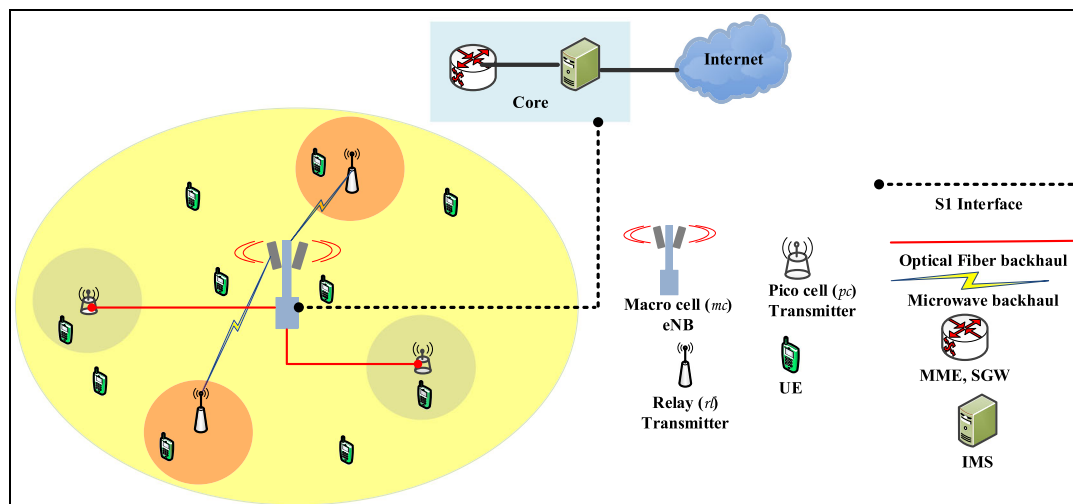

Figure 1. System model.

active users and all PRBs, respectively. We also express the transmit power for user u on PRB m as $p_u^m > 0$. It is obvious that there is only one $m \in \mathcal{M}$ for each $u \in \mathcal{U}$. Then, the maximum achievable rate obtained by Shannon theorem, $\bar{d}_u^m$, of user u on PRB m is

$$\bar{d}_u^m = W \log_2 \left(1 + \frac{p_u^m g_u^m}{I + N_0 W} \right), \tag{1}$$

where $g_{u,m} = |h_{u,m}|^2$ the channel power gain of user u on PRB m, h_m^u is the corresponding frequency response; N_0 is the single-sided noise spectral density, and I is the interference receiving from the interfering transmitter inside the HetNet architecture between similar types of small base station or low = power nodes which is assumed to be negligible. The total transmit power (P) and system throughput (D) are $P = \sum_{u=1}^{U} \sum_{m=1}^{M} p_u^m$ and $D = \sum_{u=1}^{U} \sum_{m=1}^{M} d_u^m$.

Transmission power also counts on the reciprocal of the drain efficiency of the power amplifier, which is denoted as α. The transmission power is represented as αp_u^m. Apart from the transmission power, we consider circuit power as well. From [6], circuit power, $P_{circuit}$, can be separated into two parts, one is static (fixed) part and the other is dynamic part depending on different parameters.

$$P_{circuit} = P_{static} + \delta D, \tag{2}$$

where P_s is the fixed circuit power while transmitting and δ is an invariant expressing dynamic power consumption per unit data rate.

3. THE PROBLEM FORMULATION FOR ENERGY EFFICIENCY OPTIMIZATION

Energy efficiency can be defined for a downlink OFDMA HetNet as [6]

$$EE = \frac{D}{\alpha P + P_{circuit}}. \tag{3}$$

In this paper, EE is denoted as transmitted bits per unit energy consumption (i.e., bits/Joule), where the energy consumption includes transmission or radiation energy consumption ($\alpha P \times$ transmission time (t)) and circuit energy consumption ($P_{circuit} \times t$) of transmitter. As we know, energy is the multiple of power and time.

Accordingly, the optimization problem can be formulated as in Eq. (4) as shown in the following:

$$\max_{\mathbf{d}} EE \left(\begin{array}{c} = \dfrac{\sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} d_u^m}{\alpha_1 P_{mc} + \alpha_2 \sum\limits_{n=1}^{N} P_{pc_n} + \alpha_3 \sum\limits_{n=1}^{N} P_{rl_n} + P_{static} + \delta \sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} d_u^m} \\[2em] = \dfrac{\sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} d_u^m}{\alpha_1 \left[\sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} p_u^m \right]_{mc} + \alpha_2 \sum\limits_{n=1}^{N} \left[\sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} p_u^m \right]_{pc_n} + \alpha_3 \sum\limits_{n=1}^{N} \left[\sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} p_u^m \right]_{rl_n} + P_{static} + \delta \sum\limits_{u=1}^{U} \sum\limits_{m=1}^{M} d_u^m} \end{array} \right),$$

subject to

1) $\hat{d}_u^m \leq d_u^m \leq \bar{d}_u^m$ or $d_u^m = 0$,
2) $d_u^m \geq 0$,

$$\tag{4}$$

where $\hat{d}_u^m$ denotes the minimum rate requirement for user u on PRB m. P_{mc}, P_{pc}, and P_{rl} represent the transmit power from macro, pico, and relay, respectively, whereas the coefficients α_1, α_2, and α_3 denote power consumption that calibrates with average transmitted power thanks to radio frequency amplifier and feeder losses. Static circuit power, P_s, for different types of transmitter also expressed

as $P_{static} = P_{static_{mc}} + \sum_{n=1}^{N} P_{static_{rl}} + \sum_{n=1}^{N} P_{static_{pc}}$. Our optimization variable is the rate vector $\mathbf{d}$. And also number of macro, pico, and relay transmitter is denoted by $n = \{1,2,\dots,N\}$.

The proposed optimization problem is non-convex by nature. To solve the problem using convex optimization method, we must remodel the constraints of the optimization problem. We redefine our constraints by using the approach as in [18]. The reformulation of our constraints based on non-negativity of Constraint 2, which ensures convexity of the problem, as given in the following:

$$\left(d_u^m\right) \cdot \left(d_u^m - \hat{d}_u^m\right) \cdot \left(\bar{d}_u^m - d_u^m\right) \geq 0. \tag{5}$$

From here, we then derive the four conditions and find the 1st and 3rd conditions that satisfy our constraint's non-negativity and convexity. The four conditions are

$$\begin{aligned} &\textbf{1)} \ d_u^m = 0; \quad \textbf{2)} \ d_u^m \in \left(0, \hat{d}_u^m\right); \\ &\textbf{3)} \ d_u^m \in \left[\hat{d}_u^m, \bar{d}_u^m\right]; \quad \textbf{4)} \ d_u^m \in \left(\bar{d}_u^m, +\infty\right). \end{aligned} \tag{6}$$

Now, the solution space defined by the constraints is convex, and the objective function of the proposed optimization problem is concave, thereby our problem has a solution. That means, it is a convex optimization problem [19].

4. OPTIMIZATION FOR ACHIEVING MAXIMUM ENERGY EFFICIENCY

In this section, we develop an algorithm using gradient method by constructing Lagrangian's function and satisfying the solution with KKT. Let us formulate the Lagrangian with our problem with Lagrange multiplier λ:

$$L(\mathbf{d}, \lambda) = EE + \sum_{u=1}^{U} \sum_{m=1}^{M} \lambda_u^m \left[\left(d_u^m\right) \left(d_u^m - \hat{d}_u^m\right) \left(\bar{d}_u^m - d_u^m\right)\right], \tag{7}$$

with the reciprocal Lagrange dual function

$$g(\lambda) = \max_{\mathbf{d}} L(\mathbf{d}, \lambda). \tag{8}$$

Subsequently, the dual problem is expressed in the following:

$$\min_{\lambda} g(\lambda) \ ; \ \lambda \geq 0. \tag{9}$$

Hence, the objective functions of problems (7) and (9) are differentiable, with respect to the primal variable $\mathbf{d}$ and dual variable λ, therefore these two problems can be solved by the gradient projected method [19] :

Algorithm 1 The QoS (data rate) constrained algorithm to optimize EE [23]

1: **Step 1: Initialization**
   Set $d_u^m(0)$ and $\lambda_u^m(0)$ to some non-negative value for all users u and resource blocks m.
2: **Step 2: Optimization**
   Applying gradient method.
   Update $d_u^m(i+1)$ according to Eq. (10a).
   Update $\lambda_u^m(i+1)$ according to Eq. (10b).
3: **Step 3:**
   Iterate until the implementation converges to the optimality (or the number of iteration is achieved), the algorithm stops, or else return to step 2.

$$d_u^m\left(i+1\right)=\left[d_u^m\left(i\right)+\theta\cdot\frac{\partial L\left(\mathbf{d},\lambda\right)}{\partial d_u^m}\right]^+,\tag{10a}$$

$$\lambda_u^m\left(i+1\right)=\left[\lambda_u^m\left(i\right)-\psi\cdot\frac{\partial L\left(\mathbf{d},\lambda\right)}{\partial \lambda_u^m}\right]^+,\tag{10b}$$

where i denotesthe iteration index and θ, ψ are positive step sizes, and $[\cdot]^+$ is a projection onto the set of $\mathbb{R}^+$. By setting $\frac{\partial L(\mathbf{d},\lambda)}{\partial \mathbf{d}}$ to zero (i.e., the KKT condition), one can obtain a solution. The proposed approach can be summarized in Algorithm 1.

5. SIMULATION RESULTS AND DISCUSSION

Numerical results are exhibited to demonstrate and discuss the effectiveness of the proposed method. We use a system level simulation to implement this iterative optimization and also to evaluate the convergence behavior of the proposed algorithm. We use frequency reuse one, and the entire simulation is done for downlink case.

5.1. Deployment

We consider an LTE network using hexagonal deployment with a central cell as a reference cell surrounded by six cells in the first tier and twelve cells in the second tier. To avoid border effects, wrap-around is also used. User Equipment (UEs) are deployed independently with uniform distribution throughout the cell. Monte Carlo simulation is used with full-queue traffic model for all the users, which means they always have information ready to be transmitted. Implementation in the simulator as illustrated in Figure 2, one macro cell – marked as *mc*-eNB with several number of LPNs (pico cells, marked as *pc*, and relays, marked as *rl*) – is shown for central cell. UEs are marked by cross symbol ($\times$). Each circle represents the coverage area of each transmitter.

The key parameters of the simulated system are set according to the LTE standard [24], which is summarized in Table I.
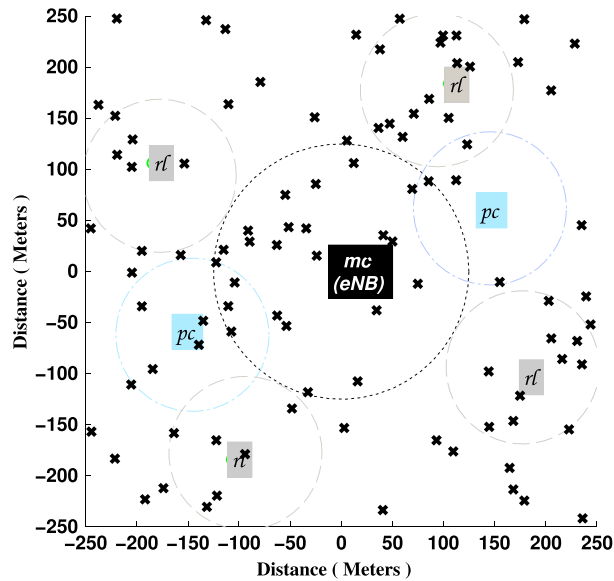

Figure 2. Deployment of one reference heterogeneous networks cell-site [21].

Table I. Simulation parameters.

Parameter	Value	
Deployment	Mobile randomly deployed at each cell	
Cellular layout	Hexagonal grid, 19 cell sites, 3 cell sectors per cell-site	
Inter-heterogeneous network distance	500 m	
Macro transmit power P_{mc}	20 Watt	
Pico transmit power P_{pc}	2 Watt	
Relay transmit power P_{rl}	1 Watt	
Static circuit power (P_s)	Macro ($P_{s_{mc}}$)	15 Watt
	Pico ($P_{s_{pc}}$)	10 Watt
	Relay ($P_{s_{rl}}$)	5 Watt
α	Macro (α_1)	3.8 [25]
	Pico (α_2) and relay (α_3)	5.5 [25]
δ	33.0103 dBm/Mbps [6]	
Carrier frequency	2.6 GHz	
Bandwidth	10 MHz	
Number of physical resource block	50	
Noise density	-174 dBm/Hz	
Path-loss model	Macro	$PL(\text{dB}) = 40\log_{10}(d) - 11.02$
	Pico and relay	$PL(\text{dB}) = 22\log_{10}(d) + 34.02$
Log-normal shadowing	Macro	4 (dB)
	Pico and relay	6 (dB)
Noise figure	7 (dB)	
Antenna gain	Macro: 14dBi, pico: 5dBi: relay: 5 dBi	
Maximum number of UEs	40 per cell	

Figure 3. Impact of the step size.

5.2. *Performance Analysis*

Figure 3 demonstrates the proposed optimization algorithm's convergence behavior with a step size of the different types of number. It can be seen that using our algorithm, the EE of the system approaches the optimal value after some iterations. Our algorithm should converge quickly enough to have a realistic implementation in a system level basis. As a result, the comparison of the different types of step size number is useful. This, Figure 3, also shows the convergence behavior of EE with two types of static step size (fractional → 0.1 and integer → 1) and dynamic decreasing step

size $1/(1+0.01 \times t)$ [18]. It can be observed that the convergence behavior with a dynamic step size $1/(1+0.01 \times t)$ is smoother but converges more slowly than the integer static step size. The convergence behavior with fractional static step size 0.2 not only demonstrates the slowest convergence but also shows property of the least smoothness. A considerable gain employing the dynamic step size is to be capable to converge rapidly first with bigger step sizes and then fine-tuning itself in the later stage with smaller step sizes.

In conclusion, we find that a static step size is more suitable and can converge more rapidly in reality but we prefer a dynamic step size because of its slow-transform rate profile, which is very important for the smoothness of system quality. Otherwise, a sudden change of the access data rate will often result in undesirable quality fluctuation.

Figure 4 demonstrates the impact of the static power factor P_{static} in our optimization algorithm. The EE is improved if we consider little static power factor P_{static} and also converges very quickly compare with the scenario when more static circuit power is considered. For this graph, we assume total static circuit power of one HetNet cell site, that is, $P_{static} = P_{static_{mc}} + P_{static_{pc}} + P_{static_{rl}}$. The value of P_{static} makes an impact on the EE; the more the P_{static} the less the EE of the system. Increasing of the P_{static} needs more iteration to converge but makes optimization smoother so that abrupt change would make less impact on the system.

Figure 5 presents the effect of different UEs PRB demands using the proposed algorithm with demands of 3 PRBs per User Equipment (UE). Increasing the number of UEs enhances the EE of the system because it increases the data rate. From the figure, we notice that the smaller the number
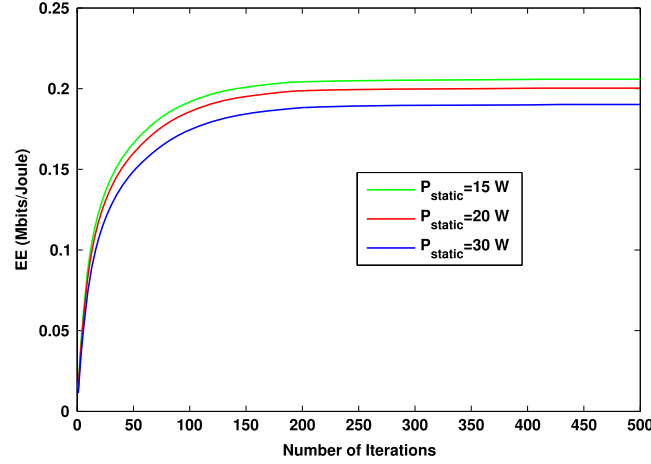

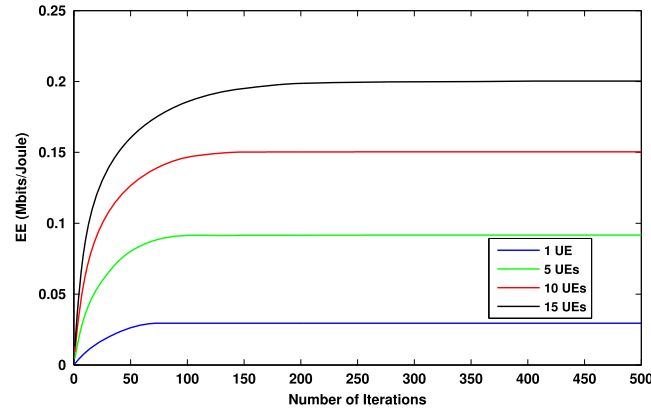Figure 4. Comparison of convergence of static circuit power.

Figure 5. Comparison of convergence of energy efficiency (EE) for different UE number.
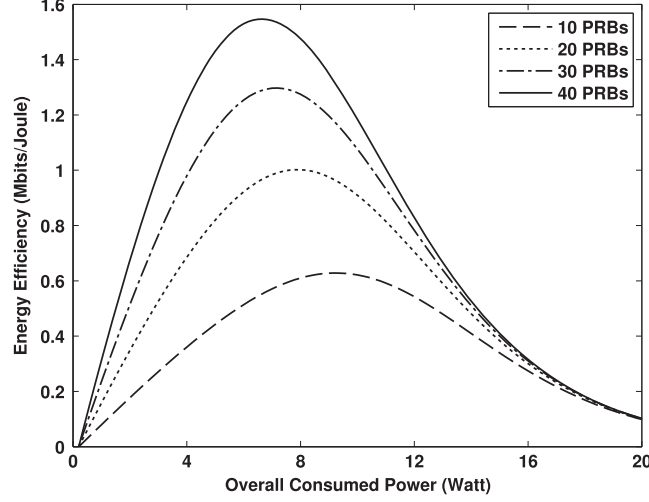
Figure 6. Relationship of energy efficiency (EE), overall consumed power, and physical resource blocks (PRBs) allocation.

of UEs the faster the algorithm goes to the convergence because more UEs means more iterations to converge. Furthermore, this means if offloading is needed in HetNet, then faster convergence of the algorithm is occurred in the lower QoS requirement while convergence becomes slower to higher QoS requirement.

For some specified power consumption value, we can deduce that the system capacity and the EE is proportionately related. That means when system capacity is higher, the EE of that system is also meant to be higher, and vice versa. This trait enables less power requirement to satisfy the demand for a defined capacity requirement. Hence, this optimization method is sensible to measure whether a wireless system is efficient in consuming energy.

For better understanding, Figure 6 shows the EE of a single user with variable consumed power for different PRB. It is pretty much evident that, maximum EE is achieved by allocating all possible PRBs and tuning the power accordingly. Figure 6 also represents the average cell EE as a function of the SE (Eq. (4)). We observe that EE increases with SE until some point and then decreases. In order to interpret this result, we need to recall that the EE is a monotonic function until circuit power is considered. The curve tends to be quasi-concave on SE which justifies the basic criterion of SE–EE curve depicted in [6]. According to [26], a function $f : Q \to \mathbb{R}$ is quasi-concave on Q if and only if for all $x, y \in Q$ and for all $\beta \in (0, 1)$ it is the case that

$$f\left[\beta x + (1 - \beta)y\right] \geqslant \min\left\{f(x), f(y)\right\}, \tag{11}$$

which justifies the quasi-concavity shown in the figure. Figure 6 also demonstrates the optimum envelop of the overall SE–EE region, which provides a complete perspective on the trade-off of SE–EE. The optimum EE emphasizes the presence of a saturation point, beyond which the EE can no longer be further enhanced, irrespective of how many extra resources are utilized. Applying this result, on one way, we can plan a HetNet system with optimal energy consumption while the system capacity is not limited. On the other way, we can optimize to achieve maximum EE while fulfilling the given SE (QoS) requirement. Therefore, to achieve more gain in terms of EE, wireless system operators should set up operational SE of the system close to the peak value of EE.

For a clear idea of the results in Figure 6, and to have a better understanding of the bandwidth, SE and EE relation, we present a three-dimensional curve to show the entire picture through the numerical analysis in Figure 7. The reason for this is considering the bandwidth, the SE, and the EE separately is not providing the clear picture efficiently. The curve is obtained with a certain assignment for 10 resource blocks, and the variable are the different numbers of bandwidth allocations and SE. As for the curve in Figure 7, we notice two features:
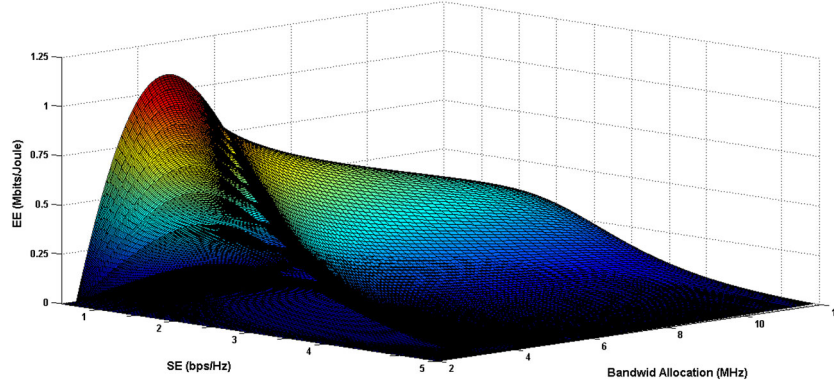
Figure 7. The energy efficiency (EE) versus the spectral efficiency (SE) and the bandwidth allocations for single mobile user scenario.
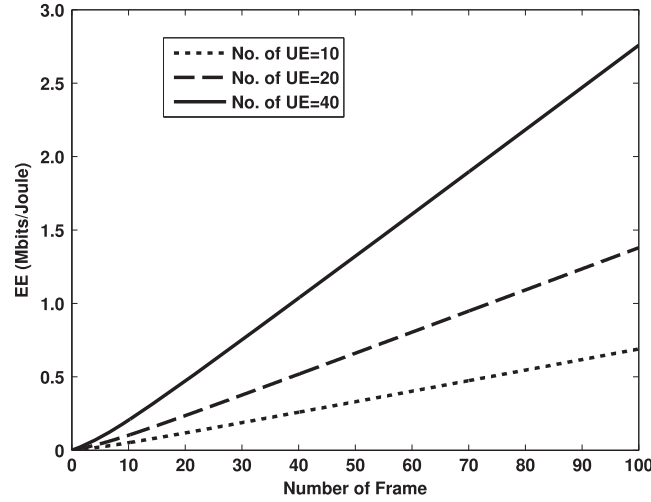

Figure 8. The energy efficiency (EE) versus the number of frame (when transmit power is constant).

- If SE is increasing, the optimal solution of EE always appears inside the feasible domain as the global optimality, but after reaching the optimality, it decreases with the SE.
- The overall curve surface is quasi-concave, and so is the curve line connected by all the boundary optimal points.

These two features can be easily extended to the curves in Figure 6, because the optimality we are concerned with is actually searched among many similar curves with various resource block assignments.

We have developed globally optimal PRB assignment policies that maximize the overall network EE. We analyze our algorithm for the different numbers of UEs in terms of transmitted frame while transmit power is constant. In Figure 8, we demonstrate relationship between the EE and the number of transmitted frame. Using the proposed optimization method, the EE is increased with the increase of the number of user although the transmit power is constant (for example, in this case, power is 20 W). The more frames we transmit, the more probability to have more EE because the increase of frame transmission ensures better utilization of the resource allocation which eventually enhances throughput.

6. CONCLUSION

In this paper, we have investigated the EE optimization problem in downlink OFDMA system for HetNet, using convex optimization theory. An optimization problem is formulated to maximize EE, where a constraint is formulated as a cubic inequality for a given data rate requirement, in which not only the radiated power but also both types of the circuit power (static and dynamic) are taken into consideration, without which the SE–EE trade-off analysis for HetNet would be incomplete. A novel-optimizing method is developed to achieve maximum EE, for radio resource allocation. The simulation results show that our algorithm converges quickly, which is crucial for the design of practical green wireless systems. Using these results, we can architect optimal energy consumption (maximize EE) networks based on QoS-oriented method for HetNet while the total power is fixed. For future research, different QoS constraint approaches need to be addressed along with the comparison of other methods.

REFERENCES

1. Fettweis G, Zimmermann E. ICT energy consumption – trends and challenges. In *Communications*. WPMC: Lapland, Finland, 2008; 2006–2009.
2. De Sanctis M, Cianca E, Joshi V. Energy efficient wireless networks towards green communications. *Wireless Personal Communications* 2011; **59**(3):537–552.
3. Damnjanovic A, Montojo J, Wei Y, Ji T, Luo T, Vajapeyam M, Yoo T, Song O, Malladi D. A survey on 3GPP heterogeneous networks. *IEEE Wireless Communications* 2011; **18**(3):10–21.
4. Miao G, Himayat N, Li Y, Bormann D. Energy efficient design in wireless OFDMA. *2008. ICC '08. IEEE International Conference on Communications*, Beijing, China, May 2008; 3307–3312.
5. Chen L, Yang Y, Chen X, Wei G. Energy-efficient link adaptation on Rayleigh fading channel for OSTBC MIMO system with imperfect CSIT. *IEEE Transactions on Vehicular Technology* 2013; **62**(4):1577–1585.
6. Xiong C, Li GY, Zhang S, Chen Y, Xu S. Energy- and spectral-efficiency tradeoff in downlink OFDMA networks. *IEEE Transactions on Wireless Communications* 2011; **10**(11):3874–3886.
7. Li Z, Jiang H, Pan Z, Liu N, You X. Energy spectral efficiency tradeoff in downlink OFDMA network. *International Journal of Communication Systems* 2014. DOI: 10.1002/dac.2725.
8. Ng D, Lo E, Schober R. Energy-efficient resource allocation for secure OFDMA systems. *IEEE Transactions on Vehicular Technology* 2012; **61**(6):2572 –2585.
9. He C, Sheng B, You X. Energy and spectral efficiency trade-off for the downlink OFDM-distributed antenna systems. *International Journal of Communication Systems* 2014; **27**(11):3339–3351.
10. He C, Sheng B, Zhu P, Wang D, You X. Energy efficiency comparison between distributed and co-located MIMO systems. *International Journal of Communication Systems* 2014; **27**(1):81–94.
11. Hasan Z, Boostanimehr H, Bhargava V. Green cellular networks: a survey, some research issues and challenges. *IEEE Communications Surveys Tutorials* 2011; **13**(4):524–540.
12. Feng D, Jiang C, Lim G, Cimini LJ, Jr., Feng G, Li GY. A survey of energy-efficient wireless communications. *IEEE Communications Surveys Tutorials* 2013; **15**(1):167–178.
13. Wang W, Shen G. Energy efficiency of heterogeneous cellular network. *2010 IEEE 72nd Vehicular Technology Conference Fall (VTC 2010-fall)*, Ottawa, Canada, September 2010; 1–5.
14. Bayer N, Sivchenko D, Einsiedler HJ, Roos A, Uzun A, Gondor S, Kupper A. Energy optimisation in heterogeneous multi-RAT networks. *2011 15th International Conference on Intelligence in Next Generation Networks (ICIN)*, Berlin, Germany, 2011; 139–144.
15. Soh YS, Quek TQ, Kountouris M, Shin H. Energy efficient heterogeneous cellular networks. *IEEE Journal on Selected Areas in Communications* 2013; **31**(5):840–850.
16. Wildemeersch M, Quek TQ, Slump CH, Rabbachin A. Cognitive small cell networks: energy efficiency and trade-offs. *IEEE Transactions on Communications* 2013; **61**(9):4016–4029.
17. Song Y, Kong PY, Han Y. Power-optimized vertical handover scheme for heterogeneous wireless networks. *IEEE Communications Letters* 2014; **18**(2):277–280.

18. Li C, Xiong H, Zou J, He Z. Joint source and flow optimization for scalable video multirate multicast over hybrid Wired/Wireless coded networks. *IEEE Transactions on Circuits and Systems for Video Technology* 2011; **21**(5): 550–564.
19. Boyd S, Vandenberghe L. *Convex Optimization*. Cambridge University Press: New York, USA, 2004.
20. Huq KMS, Mumtaz S, Rodriguez J, Verikoukis C. Investigation on energy efficiency in HetNet CoMP architecture. *2014 IEEE International Conference on Communications (ICC)*, Sydney, Australia, 2014; 1112–1117.
21. Huq KMS, Mumtaz S, Alam M, Rodriguez J, Aguiar RL. Frequency allocation for HetNet CoMP: energy efficiency analysis. *The Tenth International Symposium on Wireless Communication Systems 2013 (ISWCS 2013)*, Ilmenau, Germany, 2013; 81–85.
22. Kim J, Lee D, Sung W. Interference coordination of heterogeneous LTE systems using remote radio heads. *EURASIP Journal on Advances in Signal Processing* 2013; **2013**(1):1–8.
23. Huq K, Mumtaz S, Bachmatiuk J, Rodriguez J, Wang X, Aguiar R. Green hetnet comp: energy efficiency analysis and optimization. *IEEE Transactions on Vehicular Technology* 2014; **PP**(99):1–1.
24. 3GPP. Evolved universal terrestrial radio access (E-UTRA); further advancements for E-UTRA physical layer aspects (release 9). *Technical Report*, TR 36.814,V9.0.0, Third Generation Partnership Project, Sophia Antipolis, France, March 2010.
25. Available from: http://www.green-communications.net/globecom09/docs/GreenComm-GLOBECOM09-4-2-Fehske.pdf (accessed March 25, 2015).
26. Sundaram RK. *A First Course in Optimization Theory*. Cambridge University Press: New York, USA, 1996.