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Energy-Efficient Joint Power Allocation and Energy Cooperation for Hybrid-Powered Comp-Enabled HetNet

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ABSTRACT Base station (BS) coordination with respect to data and energy cooperation has recently emerged as a potential solution for enhancing the energy efficiency (EE) of multi-cell multi-tier cellular network architecture. This work studies the EE maximization problem in a hybrid-powered (grid and renewable energy source) heterogeneous network (HetNet) where the data and energy are jointly coordinated among the BSs. We propose a combinatorial optimization algorithm to maximize the system EE with the aim to reduce grid power consumption (GPC). Due to the complexity of the formulation, Lagrange dual decomposition and metaheuristic method are incorporated to solve the problem. Furthermore, the non-fractional programming EE problem is solved using the Dinkelbach's method which converges faster with a lower complexity. Simulation results show that cooperation among the BSs to share the channel information and energy reduces the GPC by nearly 20% and increases EE around 10% during harvested energy scarcity among the BSs.

INDEX TERMS Combinatorial optimization, CoMP-JP, energy cooperation, energy efficiency, hybrid-power.

I. INTRODUCTION

Tremendous growth in user equipment (UE) for cellular networks has caused a heavy and congested network traffic which subsequently affects data rate of the users. Heterogeneous network (HetNet) is one of the effective network layout to cater for the user demands by offloading the macro base station (MBS) traffic to the small cell base stations (SBSs) which operate at much lower power [1]. Introduction of small cells can facilitate higher data rate transmission, but it triggers some other issues including inter-cell interference (ICI) between the macrocell and small cells (cross-tier) and among the small cells (co-tier) in the case of user sharing the same set of spectrum. Nonetheless, with appropriate coordination among the base stations, both types of interference can be eliminated. One such efficient technique is called coordinated multi-point joint-processing (CoMP-JP) [2] where base stations coordinate with each other to transmit data to the users (data cooperation) not only to strengthen the desired signal but also to mitigate the interference.

However, CoMP-JP comes with some drawbacks, especially the increased energy consumption caused by coordination among multiple base stations. As a measure to reduce the grid power consumption (GPC) which causes higher carbon footprint, renewable energy (RE) sources are considered as an alternative to power the cellular networks. However, due to the irregularity of RE resources, grid power source is still relied to sustain the quality of cellular service [3]. Furthermore, each harvesting base station in the HetNet has different harvesting capability and the non-uniform distribution of users in each cell will eventually lead to unbalanced usage of the harvested RE. Since grid power is a precious resource while the RE is a scarce resource, an efficient energy cooperation framework is required to manage the sharing of harvested energy among base stations from different network tiers in order to reduce the GPC. In this paper, we aim to maximize the energy efficiency (EE) of a cellular HetNet which is capable to enforce cooperation among the base stations to

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TABLE 1. Summary of the relevant work which employs hybrid energy source.

Related Work	Problem	Optimization technique	Main objective	Data cooperation	Energy cooperation
Y. Zhang *et al.* [9]	Power allocation	Lagrange dual decomposition & heuristic scheme	Maximize throughput	No	No
P.H. Chiang *et al.* [10]	Resource allocation	Lyapunov optimization	Reduce GPC	No	No
R. Thakur *et al.* [11]	Energy cooperation & cell selection	Power spreading scheme	Minimize GPC	No	Yes
A. Jahid *et al.* [12]	Utilization of the green energy & grid energy consumption	JT CoMP	Improve EE	Yes	No
A. Jahid *et al.* [13]	Hybrid energy usage & UE association	DPS CoMP	Improve EE	Yes	No
Proposed algorithm	Power allocation & energy exchange	Lagrange dual decomposition & metaheuristic	Maximize EE	Yes	Yes

effectively send data to users as well as to efficiently share the energy among the base stations under different harvesting scenarios.

Energy management and cooperation have been extensively studied in the literature. The work in [4] has developed an optimal energy management framework for energy internet by considering a realistic renewable energy resource model. The authors in [5] have invented a novel technique to assess the stability of microgrid used to manage and distribute the RE. Furthermore, a cooperative energy management scheme has been presented in [6] where cooperation among energy bodies (suppliers and customers) is enforced to alleviate the RE fluctuation. However, the energy management schemes in [4]–[6] are not specifically designed for HetNets which necessitate an energy cooperation mechanism not only to maximize the EE, but also ensure quality of service for all UEs.

Thus far, the existing works related to energy cooperation for HetNets mainly focus on either throughput maximization [7] or cost minimization [8]. A general review of some recent relevant works which employ hybrid energy supplies (i.e. grid power and RE source) is presented in Table 1. The work in [9] and [10] focus on throughput maximization and grid power reduction, respectively, without considering joint data and energy cooperation. Some recent works like [11] incorporates energy and cost awareness into similar type of network but data cooperation is not considered. Though the authors of [12] and [13] have improved the EE of the system using data cooperation, energy cooperation is not the main focus of this work. To the best of our knowledge, this is the first work which maximizes the EE of a hybrid-powered HetNet with both data and energy cooperation using a novel combinatorial (subgradient-metaheuristic) optimization technique.

The main contributions of this paper are as follows:

- Design a hybrid-powered CoMP-enabled HetNet framework by integrating energy cooperation and data coordination among the base stations to reduce GPC and mitigate interference among the cells.

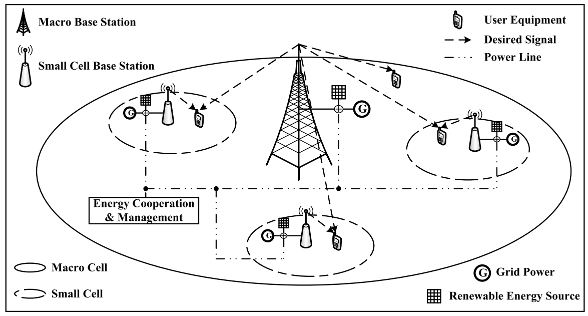

FIGURE 1. HetNet with data and energy cooperating hybrid-powered MBS and SBSs.

- Formulate a new EE optimization problem for a hybrid-powered CoMP-enabled HetNet by allowing base stations to cooperatively allocate their transmit powers and share their harvested energy subject to the minimum quality-of-service requirement.
- Develop an energy-efficient joint power allocation and energy cooperation algorithm by combining subgradient and metaheuristic methods to reduce the problem complexity. The Dickelbach's algorithm is also adopted to ensure faster convergence speed.
- Propose a metaheuristic optimization method to solve energy cooperation problem in order to simultaneously maximize EE and reduce the total GPC by means of sharing the harvested energy among the BSs.

The remainder of this paper is structured as follows. Section II describes the CoMP-based HetNet model as well as the details of the problem formulation and algorithm. Performance evaluation results are presented and discussed in Section III. Finally, the paper is concluded in Section IV.

II. SYSTEM MODEL & PROBLEM FORMULATION

Fig. 1 illustrates the system model considered in this work. The HetNet consists of a macrocell and multiple small cells with each base station powered by hybrid sources (i.e. grid power and RE source). In other words, each BS is equipped with harvesting facilities. The MBS coordinates with each SBS to serve the users within their coverage through CoMP-JP technique. Typically, the harvesting capability of MBS is considered higher compared to SBS. Therefore, each base station shares the RE source among each other for a balanced usage. The BSs are indexed as j and $\mathbf{J}$ refers to the set of BSs in the network, UEs are indexed as i.

TABLE 2. List of main variables and parameters.

Notations	Descriptions
R_i	Data rate
B_o	Bandwidth
N_o	Noise power
p_{ji}	Transmit power from BS j to user i
p^g_{ji}	Transmit power drawn from grid by BS j to user i
p^h_{ji}	Transmit power drawn from RE source by BS j to user i
g_{ji}	Channel gain from BS j to user i
P^{EH}_j	Total green power drawn by BS j
E_j	Harvested renewable energy at BS j
P_{Total}	Net on-grid power consumption
P^{cir}_j	Cicuit power of BS j
e_j	Energy transferred among BSs $-e_j$: transferred from BS j $+e_j$: received by BS j
ρ	Energy transfer efficiency
λ_j	Power amplifier efficiency
E^{HC}_M	Energy harvested by MBS
E^{HC}_S	Energy harvested by SBSs

Table 2 lists out the notations of the main variables and parameters used throughout the paper. The parameters used in the problem formulation which includes the throughput of UE i denoted as R_i, GPC denoted as P^{Total} and power drawn from RE source by BS j denoted as P^{EH}_j can be expressed as follows:

$$R_i = B_o \log_2 |1 + \frac{\sum_j p_{ji} g_{ji}}{B_o N_o}| \tag{1}$$

$$p_{ji} = p^g_{ji} + p^h_{ji} \tag{2}$$

$$P^{Total} = \sum_j \left[\frac{1}{\lambda_j} \sum_i p^g_{ji} + P^{cir}_j \right] \tag{3}$$

$$P^{EH}_j = E_j + \rho e_j \tag{4}$$

A. PROBLEM FORMULATION

An optimization problem is formulated to maximize EE of the system with the aim to reduce the total GPC. EE in this case is defined as ratio of the system throughput to the total grid power consumption [14]. The objective function and constraints are formulated as follows:

$$\max_{\{p_{ji}\},\{e_j\}} \; EE = \frac{\sum_i R_i}{P^{Total}} \tag{5}$$

$$s.t. \; \sum_i p^h_{ji} \leq P^{EH}_j, \quad \forall j, \tag{5a}$$

$$\sum_i p_{ji} \leq P_{j,max}, \quad \forall j, \tag{5b}$$

$$\frac{\sum_j p_{ji} g_{ji}}{B_o N_o} \geq SNR_{i,thr}, \quad \forall i, \tag{5c}$$

$$-E_j \leq e_j \leq \sum_{k \in \mathbf{J} \setminus \{j\}} E_k, \quad \forall j, \tag{5d}$$

$$\sum_j e_j = 0 \tag{5e}$$

Constraint (5a) ensures that the transmit power drawn from RE source does not exceed the total RE of BS j. Next, constraint (5b) ensures the total transmission power used by BS j to all users within its cell is below the maximum permissible transmit power, $P_{j,max}$. The constraint in (5c) sets a quality-of-service requirement on user i with minimum signal-to-noise ratio (SNR) of user i, $SNR_{i,thr}$. Constraint (5d) sets the possible range of exchanged energy for BS j based on the harvested energy of each BS. It is noteworthy that $e_j < 0$ shows that BS j shares its harvested energy to others, while $e_j > 0$ implies that BS j receives harvested energy from others. Finally, constraint (5e) ensures that the total energy exchanged among BSs must be always zero (i.e. equilibration of transferred and received energy).

B. DUAL DECOMPOSITION

The formulated problem in (5) is decomposed into two parts for simplicity, power allocation (PA) and energy cooperation (EC) where the former is tackled using Lagrange dual decomposition whereas a metaheuristic method is used for the latter.

First, the Lagrangian function of the optimization problem is expressed as below:

$$\begin{aligned} \mathscr{L}(p_{ji}, e_j) = & \sum_i B_o \log_2 \left(1 + \frac{\sum_j p_{ji} g_{ji}}{B_o N_o} \right) \\ & - \tau \left(\sum_j \left[\frac{1}{\lambda_j} \sum_i p^g_{ji} + P^{cir}_j \right] \right) \\ & - \gamma_j \left[\sum_i p^h_{ji} - E_j - \rho e_j \right] \\ & - \alpha_j \left[\sum_i p_{ji} - P_{j,max} \right] \\ & - \beta_i \left[SNR_{i,thr} - \frac{\sum_j p_{ji} g_{ji}}{B_o N_o} \right] \end{aligned} \tag{6}$$

where γ_j, α_j, and β_i are nonnegative Lagrange multipliers and τ represents EE based on Dinkelbach's method [15] (see Appendix A).

Next, the dual problem is expressed as below:

$$\min_{\gamma_j, \alpha_j, \beta_i \geq 0} \max_{p_{ji}} \mathscr{L}(p_{ji}) \tag{7}$$

Then, the dual problem is solved by solving the corresponding Karush-Kuhn-Tucker (KKT) conditions [16]:

$$\frac{d\mathscr{L}}{dp^*_{ji}} = 0 \tag{8}$$

where p^*_{ji} is the optimal power allocation.

Finally, the optimal transmit power obtained from Dual Decomposition Method (see Appendix B):

$$p_{ji}^{*} = \left[\frac{B_o}{(\ln 2)\left(\frac{\tau}{\lambda_j} + \gamma_j + \alpha_j - \beta_i \frac{\sum_j g_{ji}}{B_o N_o}\right)} - \left(\frac{B_o N_o}{\sum_j g_{ji}}\right) \right]^{+} \quad (9)$$

C. COMBINATORIAL OPTIMIZATION ALGORITHM

The EE problem in (5) can be classified as a nonlinear fractional programming problem and therefore it is much complicated to be solved using regular mathematical approaches. Thus, a low-complexity Dinkelbach based iterative algorithm [15] is used to solve the problem as shown in Algorithm 1. Unless the convergence condition is satisfied where optimal EE τ^* is achieved, the obtained EE or τ is used to solve the next iteration as can be seen from steps 16-22 of Algorithm 1.

Algorithm 1 PAEC Algorithm

1: Set maximum number of iterations T_{out}; convergence condition ϵ & $\tau^{(1)} = 0$
2: Set iteration index, $n = 1$
3: **for** $1 \leq n \leq T_{out}$ **do**
4: Initialize Lagrange multipliers to an arbitrarily large positive value
5: Set *min* & *max* exchange energy, $-E_j \leq e_j \leq \sum_{k \in \mathbf{J} \setminus \{j\}} E_k$
6: Update power allocation (obtained from dual decomposition, Eq.9)
7: $e_j^* = random\ integer\ [min\ max]$; $\sum_j e_j^* = 0$
8: **if** $\sum_i p_{ji}^h - E_j \leq e_j^*$ **then**
9: $max = e_j^*$
10: **else**
11: $min = e_j^*$
12: **end if**
13: Evaluate Lagrangian function (of the primal objective function) $f(n)$, Eq.6
14: Update Lagrange multipliers with small positive step size $\delta(n)$:
$\gamma_j^{(n+1)} = [\gamma_j^{(n)} - \delta(n) * (P_j^{EH} - \sum_i p_{ji}^h)]^+$
$\alpha_j^{(n+1)} = [\alpha_j^{(n)} - \delta(n) * (P_{j,max} - \sum_i p_{ji})]^+$
$\beta_i^{(n+1)} = [\beta_i^{(n)} - \delta(n) * (\frac{\sum_j p_{ji} g_{ji}}{B_o N_o} - SNR_{i,thr})]^+$
15: Repeat steps 6-14 until $|f(n+1) - f(n) \leq \epsilon|$ or exceeds maximum number of iterations
16: **if** $R(p^{(n)}, e^{(n)}) - \tau^{(n)} P^{Total}(p^{(n)}, e^{(n)}) < \epsilon$ **then**
17: *set* $\tau^* = \tau^{(n)}$
18: break
19: **else**
20: *set* $\tau^{(n+1)} = \frac{R(p^{(n)}, e^{(n)})}{P^{Total}(p^{(n)}, e^{(n)})}$
21: $n = n + 1$
22: **end if**
23: **end for**

Subgradient method is preferred over the gradient method despite being slower than the latter due to its simplicity [17]. Steps 13-15 of Algorithm 1 show how subgradient method is combined with dual decomposition technique and used to find each value of the Lagrange multipliers and subsequently update the value of allocated power for each user served by respective base stations. Power allocation and energy exchanged values are updated in each loop and used to evaluate the derived Lagrangian function and update the lagrange multipliers. The process is repeated till the difference between the current and previous Lagrangian function value falls below the convergence threshold.

While subgradient method is employed to solve the power allocation part of the problem, a metaheuristic method is adopted to find the optimal energy exchanged e_j^* of the base stations as shown in steps 7-12 of Algorithm 1. As mentioned, power allocation and energy cooperation (PAEC) are combined as a combinatorial optimization problem which is more complex to be solved using optimization or iterative algorithm. Instead, metaheuristic method is used, though a global optimal solution could not be ensured, a near-optimal solution can still be attained at much lower complexity [18]. A random value that satisfies (5d) is chosen from the range of exchanged energy of each BS which is set according to (5e) (i.e. minimum and maximum amount of energy that can be transferred to and received from other BSs). Depending on condition in (5a), the minimum or maximum exchanged energy is varied based on the chosen value and the process repeats till convergence is achieved.

III. RESULTS & DISCUSSION

The optimization technique is applied on three types of systems namely non-coordinated multipoint (Non-CoMP), coordinated multipoint with only power allocation technique (CoMP-PA) and with both power allocation and energy cooperation techniques (CoMP-PAEC). It is worth noting that the Non-CoMP system incorporates PAEC technique as well. For a Non-CoMP system, each user is served by the respective BS whereas for a CoMP system, the macrocell users are served only by the MBS and small cell users are served by both MBS and their respective SBS. Unless otherwise specified, the network considered in this work generally consists of a MBS, 3 SBSs and 20 UEs per cell. Table 3 tabulates the simulation settings used in this work.

Fig. 2 depicts the convergence behavior of Dinkelbach's algorithm considered in Algorithm 1. Owing to the fast convergence characteristic of Dinkelbach's algorithm, on the average, the algorithm only requires 5 iterations to converge. The EE performance of the CoMP-PAEC scheme is about 15% better than that of the CoMP-PA scheme due to the vital role played by energy cooperation to share the harvested energy. Consequently, the GPC reduces while enhancing the EE, especially when more power is needed to cater for the increasing number of UEs.

Fig. 3 illustrates the impact of number of UEs and SBSs on the EE of all three types of systems. It is observed that the EE increases as the number of UEs or SBSs increases. This is due to the fact that the total sum rate increases at a rate faster

TABLE 3. Setting of the simulation parameters.

Parameter	Setting
System bandwidth	10MHz
Noise power density	-174dBm/Hz
Radius of macrocell Radius of small cells	500m 40m
Path loss models	MBS: 128.1 + 37.6 log(d_{km}) dB SBS: 140.7 + 36.7 log(d_{km}) dB
Channel fading model	exponentially distributed Rayleigh zero mean & unit variance
Shadowing model	iid log-normal zero mean & 10 dB standard deviation
Efficiency of power amplifier	MBS: 39% SBS: 7%
Static power	MBS: 130W SBS: 6.8W

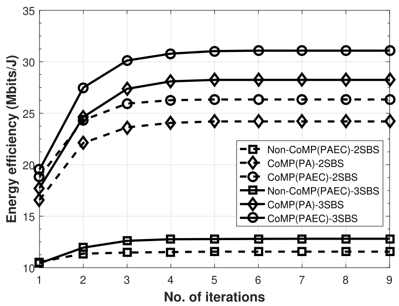

FIGURE 2. Convergence behaviour of Algorithm 1 for E_M^{HC} = 10dB and E_S^{HC} = 2dB.

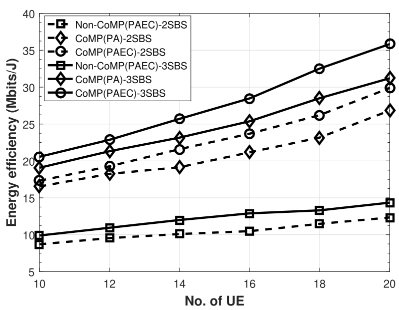

FIGURE 3. EE for different number of UEs/cell with E_M^{HC} = 10dB and E_S^{HC} = 2dB.

than the GPC, leading to better EE. There is a remarkable difference between EE of CoMP and Non-CoMP techniques as lack of coordination among the BSs causes ICI in the latter.

Figs. 4 and 5 illustrate the mutual relationship between EE and GPC for various harvesting scenarios. In Fig. 4, a proportionate harvesting situation (i.e. identical contribution of MBS and SBSs to the total harvested energy) is considered. Despite a considerable increase of about 10% in EE for the simulated scenarios, GPC reduces at a much higher rate, especially when the total harvested energy is 18dB. About 15% reduction of GPC can be seen in CoMP-PAEC technique compared to CoMP-PA and this verifies that the effectiveness of energy cooperation in reducing GPC is one of the prime contributors to the EE enhancement.

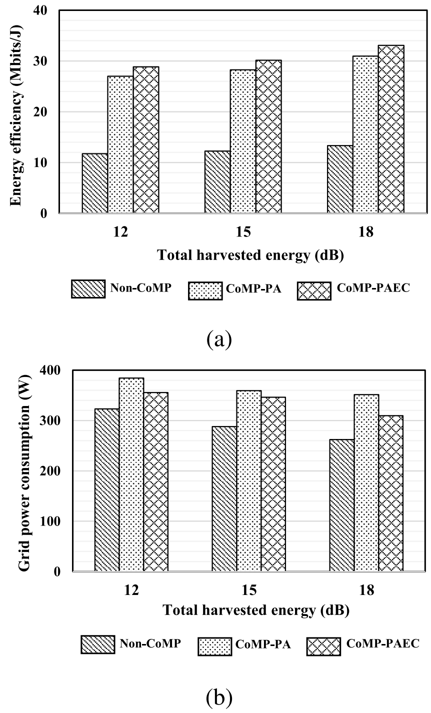

FIGURE 4. (a) EE (b) GPC for proportionate harvesting among BSs.

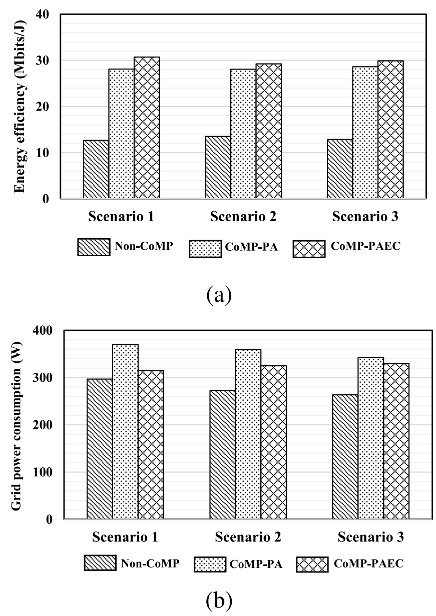

FIGURE 5. (a) EE (b) GPC for diverse harvested energy among BSs. Scenario 1: E_M^{HC} = 10dB and E_S^{HC} = 0dB, Scenario 2: E_M^{HC} = 6dB and E_S^{HC} = 5dB, Scenario 3: E_M^{HC} = 10dB and E_S^{HC} = 8dB.

Due to the environmental factors, practically, BSs harvest at different rates [19]. Fig. 5 depicts the impact of energy cooperation for different harvesting rate of MBS and SBSs. Compared to the uniform harvesting rates, it is evident that the contradistinctive harvesting rates shows a higher EE as well as an apparent drop in the GPC. Harvested energy is shared

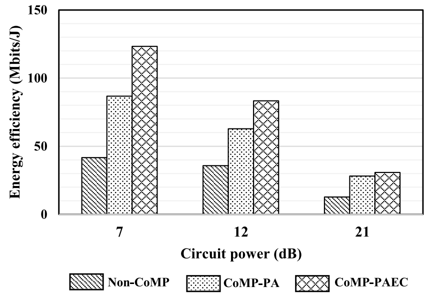

FIGURE 6. Impact of circuit power on EE for $E_M^{HC} = 10$dB and $E_S^{HC} = 2$dB.

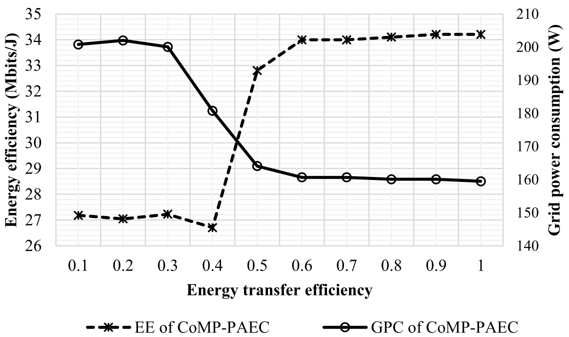

FIGURE 7. Effects of ETE on EE and GPC for $E_M^{HC} = 10$dB and $E_S^{HC} = 2$dB.

among the BSs such that the GPC is reduced substantially while sustaining EE. In other words, the effect of PAEC technique can be observed distinctly during scarcity of harvested energy (about 20% reduction in GPC).

Fig. 6 shows the effects of circuit power on EE. As the circuit power reduces, the superiority of PAEC scheme can be noticed obviously. When the circuit power is 7dB, the CoMP-PAEC scheme is found to exhibit a performance gain of around 40% in terms of EE over the CoMP-PA counterpart. This proves that high circuit power ($P_j^{cir} > 21$dB) dominates the EE of the system as it contributes the most to total power consumption, hence limiting the performance of the proposed scheme.

To gain further insight into the effects of losses incurred due to the resistive power line [20] on the proposed algorithm, Fig. 7 illustrates the plot of EE and GPC against energy transfer efficiency (ETE). At higher ETE region ($\rho \geq 0.5$), it is noticed that the EE increases by 20% and GPC reduces by 10%. High ETE improves the EE because larger amount of energy that has been transferred through the line without loss provides a bigger optimization margin and it is clearly demonstrated that the proposed algorithm performs much better in terms of EE and GPC under this scenario. However, for ETE which is lower than 0.45, most of the energy is wasted in the line loss, so less energy saving is achieved resulting in lower EE. Besides that, at lower ETE region ($\rho < 0.5$), decrease in GPC does not greatly affect EE as both the GPC and throughput improvement occurs relatively at the same rate. This verifies that line losses need to be taken into consideration as well while analyzing the energy efficiency of the system.

IV. CONCLUSION

This work proposes an energy-efficient joint power allocation and energy cooperation scheme for CoMP-based HetNet with hybrid-power sources. By using a combinatorial (subgradient-metaheuristic) optimization technique, joint cooperation of data and energy (CoMP-PAEC) yields about 10% higher EE and 20% grid power reduction compared to the non-cooperative systems (CoMP-PA). The use of Dickelbach's algorithm in the optimization problem yields a faster convergence speed. Enhanced use of harvested energy by employing energy storage device and off-grid base stations is left for future investigation.

APPENDIXES

APPENDIX A

APPLICATION OF DINKELBACH'S METHOD

Nonlinear fractional programming problem transformation:

$$\tau = \frac{\sum_i R_i(p_{ji}, e_j)}{P^{Total}(p_{ji}, e_j)}$$

$$\tau^* = \max_{\{p_{ji}, e_j\}} \frac{\sum_i R_i(p_{ji}, e_j)}{P^{Total}(p_{ji}, e_j)} = \frac{\sum_i R_i(p_{ji}^*, e_j^*)}{P^{Total}(p_{ji}^*, e_j^*)}$$

where τ^*, p_{ji}^*, and e_j^* denotes optimal EE, optimal PA, and optimal energy exchanged, respectively.

$$\begin{aligned} \max_{\{p_{ji}, e_j\}} \sum_i R_i(p_{ji}, e_j) - \tau^* P^{Total}(p_{ji}, e_j) &= \sum_i R_i(p_{ji}^*, e_j^*) - \tau^* P^{Total}(p_{ji}^*, e_j^*) \\ &= 0 \end{aligned}$$

APPENDIX B

DERIVATION OF OPTIMAL TRANSMIT POWER

Derive the Lagrangian function $\mathscr{L}$, then differentiate the Lagrangian function with respect to transmit power p_{ji}, and equate $\frac{d\mathscr{L}}{dp_{ji}^*}$ to zero:

$$\begin{aligned} \mathscr{L} = &\frac{\sum_i B_o \sum_j g_{ji}}{B_o N_o} - \tau \sum_j \frac{1}{\lambda_j} \sum_i p_{ji}^g - \tau \sum_j P_j^{cir} \\ &-\gamma_j \sum_i p_{ji}^h + \gamma_j E_j + \gamma_j \rho \sum_j e_j - \alpha_j \sum_i p_{ji} \\ &+\alpha_j P_{j,max} - \beta_i SNR_{i,thr} + \beta_i \frac{\sum_i B_o \sum_j g_{ji}}{B_o N_o} \end{aligned}$$

$$\begin{aligned} \frac{d\mathscr{L}}{dp_{ji}^*} = &\frac{\frac{\sum_i B_o \sum_j g_{ji}}{B_o N_o}}{(\ln 2)\left(B_o N_o + \sum_j p_{ji} g_{ji}\right)} - \frac{\tau}{\sum_j \lambda_j} - \gamma_j - \alpha_j \\ &+\beta_i \frac{\sum_j g_{ji}}{B_o N_o} \end{aligned}$$

$$\frac{d\mathscr{L}}{dp_{ji}^{*}} = 0$$

$$p_{ji}^{*} = \left[\frac{B_o}{(\ln 2)\left(\frac{\tau}{\lambda_j} + \gamma_j + \alpha_j - \beta_i \frac{\sum_j g_{ji}}{B_o N_o}\right)} - \left(\frac{B_o N_o}{\sum_j g_{ji}}\right) \right]^{+}$$

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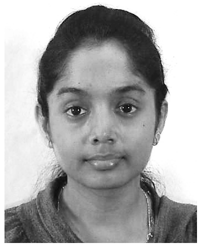

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