Cooperative Energy Trading in CoMP Systems Powered by Smart Grids

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Abstract—This paper studies the energy management in the coordinated multi-point (CoMP) systems powered by smart grids, where each base station (BS) with local renewable energy generation is allowed to implement the two-way energy trading with the grid. Due to the unevenly generated renewable energy over distributed BSs and in general the difference in the prices for buying/selling energy from/to the grid, it is beneficial for the cooperative BSs to jointly manage their energy trading with the grid and energy consumption in CoMP based communication for reducing the total energy cost. We consider the downlink transmission in one CoMP cluster by jointly optimizing the BSs’ purchased/sold energy units from/to the grid and their cooperative transmit beamforming, so as to minimize the total energy cost subject to the given quality of service (QoS) constraints for the users. By applying techniques from convex optimization and uplink-downlink duality, we propose an efficient algorithm to solve this problem optimally. Through simulations, we show the performance gain achieved by our proposed joint energy trading and communication cooperation scheme in terms of cost reduction, as compared to a baseline scheme which separately designs communication cooperation and energy trading.

I. INTRODUCTION

Due to the explosive increase of mobile data traffic, cellular operators are to deploy base stations (BSs) more densely for providing higher capacity to subscribers. However, this gives rise to more severe inter-cell interference (ICI). Therefore, coordinated multi-point (CoMP) transmission has emerged as one promising technique for next generation wireless networks (see [1] and the references therein), where multiple BSs cooperatively serve a group of distributed users by implementing baseband coordination to make use of the ICI for coherent signal combining.

On the other hand, another challenge faced by cellular operators is their drastically increasing operational costs due to the on-grid energy consumption by the growing number of BSs. Among assorted solutions proposed to overcome this issue, equipping BSs with energy harvesters that can harvest energy from the environmental sources, e.g., solar and wind, is a promising solution since the cost of renewable energy generation is in general much lower than that of the conventional energy from the grid [2]. Furthermore, with the advancing of smart grid technologies, distributed loads (e.g., BSs) that connect to the grid can be enabled with the two-way energy trading with the grid [3–5] to more flexibly utilize its locally generated renewable energy, such that in the case of renewable energy surplus, a BS can sell its excessive energy to the grid to make profit, while in the opposite case of renewable energy deficit, the BS can buy additional energy from the grid to maintain its reliable operation.

In this paper, we pursue a unified study of CoMP based communication cooperation and two-way energy trading enabled energy cooperation in a cellular system powered by smart grids, where each BS is equipped with one or more energy harvesting devices (wind-turbines and/or solar panels), and is allowed to implement the two-way energy trading with the grid using its locally generated renewable energy. In practice, due to the differences in BS locations as well as the different types of energy harvesting devices used, the renewable generation rates are uneven over distributed BSs; while due to different energy supply and demand conditions in the grid, the prices for each BS to buy and sell one unit of energy from/to the grid are also in general different [6]. Therefore, it is beneficial for the cooperative BSs to jointly manage their energy trading with the grid and energy consumption in CoMP transmission to reduce the total energy cost, which motivates this work.

For the purpose of exposition, we consider the downlink transmission in one CoMP cluster, where a group of multiple-antenna BSs each with local renewable energy generation cooperatively transmit to a set of single-antenna users by applying linear transmit beamforming. We jointly optimize the BSs’ purchased/sold energy units from/to the grid and their cooperative transmit beamforming, so as to minimize the total energy cost of the BSs subject to the given quality of service (QoS) constraints for the users. By applying techniques from convex optimization [6] and uplink-downlink duality [7], we propose an efficient algorithm to solve this problem optimally. Furthermore, we show by simulations the promising performance gain achieved by our proposed joint energy trading and communication cooperation scheme in terms of cost reduction, as compared to a baseline scheme which separately designs communication cooperation and energy trading.

It is worth noting that there have been several recent studies on improving the energy efficiency of cellular networks by taking advantage of other smart grid capabilities (versus the two-way energy trading) [8–11]. [8] jointly optimized the utilities of both the cellular network and the power network. [9–11] considered another form of energy cooperation to resolve the problem of geographically imbalanced energy demand and renewable supply, where distributed BSs exchange their locally harvested energy with each other via the dedicatedly deployed power lines [9, 10] or via the grid infrastructure [11].

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider practical cluster-based CoMP systems by focusing our study on one cluster, in which $N > 1$ BSs each
equipped with $M \geq 1$ antennas cooperatively send independent messages to $K$ single-antenna mobile terminals (MTs) (see Fig. 1 for the example of a two-BS CoMP system with $N = 2$). For convenience, we denote the set of MTs and that of BSs as $K = \{1, \ldots, K\}$ and $\mathcal{N} = \{1, \ldots, N\}$, respectively. We assume that each BS is locally equipped with one or more energy harvesting devices (wind-turbines and/or solar panels), and is also connected to the power grid with two-way energy trading. We also assume that there is a central unit deployed for each CoMP cluster which coordinates the cooperative energy trading as well as the cooperative communication within the cluster. To implement that, the central unit needs to collect both the communication data (i.e., the transmit messages and channel state information (CSI)) from each of the BSs through the cellular backhaul links, and the energy information (i.e., the energy harvesting rates and energy buying/selling prices) from these BSs via the smart meters installed at BSs and the grid-deployed communication/control links connecting them.

We assume block-based transmissions and quasi-static models for both the renewable energy processes and wireless channels, where the energy harvesting rates and the channel coefficients remain constant during each communication block and may change from one block to another. This is valid in practice, since the coherence time of a wireless channel (say, several milliseconds) is usually much smaller than that of an energy harvesting process (e.g., a few tens of seconds for solar and wind power). For convenience, each block duration is normalized to unity unless otherwise specified; thus, the terms “energy” and “power” will be used interchangeably in the sequel. From a practical cost consideration, we do not consider storage devices used at each of the BSs in this paper due to their high deployment cost; as a result, each BS will either consume all of its available energy or sell to the grid during each block. This simplifies our analysis to one particular block for investigation. Next, we explain the energy management model at the BSs, then present the downlink CoMP transmission model, and finally formulate the optimization problem for joint energy trading and communication cooperation.

### A. Energy Management Model

As assumed above, each BS is equipped with energy harvesting devices and is also connected to the grid for two-way energy trading. We denote the harvested energy at each BS $i \in \mathcal{N}$ as $E_{i} > 0$, which is a given constant for one block of our interest. We also denote the energy purchased (sold) from (to) the grid at BS $i$ as $G_{b,i} \geq 0$ ($G_{s,i} \geq 0$). When each BS $i$ buys (sells) one unit energy from (to) the grid, we denote the price that it needs to pay to (or will be paid by) the grid as $\alpha_{b,i} > 0$ ($\alpha_{s,i} > 0$). Then we have the net energy cost at BS $i$ as

$$C_{i} = \alpha_{b,i}G_{b,i} - \alpha_{s,i}G_{s,i}, i \in \mathcal{N}.$$  

(1)

Note that $C_{i}$ can be positive (e.g., $G_{b,i} > 0, G_{s,i} = 0$), negative (e.g., $G_{b,i} < 0, G_{s,i} = 0$), or zero. In practice, to prevent any BS from buying the energy from the grid and then selling back to it to make non-justifiable profit which leads to energy inefficiency, the grid operator should set $\alpha_{b,i} \leq \alpha_{b,i}, \forall i \in \mathcal{N}$, as a result we have that at most one of $G_{b,i}$ and $G_{s,i}$ can be strictly positive (otherwise, the cost in (1) can be further reduced by setting $G_{b,i} \leftarrow G_{b,i} - G_{s,i}$ and $G_{s,i} \leftarrow 0$ if $G_{b,i} \geq G_{s,i} > 0$, or $G_{b,i} \leftarrow G_{b,i} - G_{b,i}$ and $G_{s,i} \leftarrow 0$ if $G_{s,i} \geq G_{b,i} > 0$). Moreover, the energy selling price is usually subject to a minimum value, given by $\alpha_{\text{min}} > 0$, to encourage the renewable generation investment at the BSs; while the energy buying price cannot exceed the maximum electricity price in the grid, given by $\alpha_{\text{max}} > 0$. Thus, we have

$$0 < \alpha_{\text{min}} \leq \alpha_{b,i} \leq \alpha_{b,i} \leq \alpha_{\text{max}}, \forall i \in \mathcal{N}.$$  

(2)

In cellular systems, the power consumption at each BS typically includes both the transmission power due to radio frequency (RF) power amplifiers (PAs), and the non-transmission power due to other components such as cooling systems, baseband units (BBU) for data processing, and circuits of RF chains (see Fig. 1). We denote the radiated transmit power of each BS $i$ by $P_{t,i} \geq 0$, and generally model the non-transmission power as a constant denoted by $P_{c,i} > 0$. By combining them, we obtain the total power consumption at BS $i$, denoted by $P_{i}$, which should be no larger than the total energy available at BS $i$, i.e.,

$$P_{i} = P_{t,i} + P_{c,i} \leq E_{i} + G_{b,i} - G_{s,i}, i \in \mathcal{N},$$  

(3)

where $\eta > 0$ denotes the PA efficiency. Since $\eta$ is a constant, we normalize it as $\eta = 1$ unless stated otherwise.

### B. Downlink CoMP Transmission

Next, we present the downlink CoMP transmission among the $N$ BSs in one cluster. We denote the channel vector from BS $i$ to MT $k$ as $h_{ik} \in \mathbb{C}^{M \times 1}, i \in \mathcal{N}, k \in \mathcal{K}$, and the channel vector from all $N$ BSs in the cluster to MT $k$ as $h_{b,k} = [h_{1,k}^{T} \ldots h_{N,k}^{T}]^{T} \in \mathbb{C}^{MN \times 1}, k \in \mathcal{K}$, with the superscript $T$ denoting the transpose. We consider linear transmit beamforming applied at the BSs. Let the information signal for MT $k \in \mathcal{K}$ be denoted by $s_{k}$ and its associated beamforming vector across all BSs by $w_{k} \in \mathbb{C}^{MN \times 1}$. Then the transmitted signal for MT $k$ can be expressed as

$$x_{k} = w_{k}s_{k},$$

where $s_{k}$ is assumed to be a complex random variable with zero mean and unit variance. Thus, the received signal at MT $k$ is given by

$$y_{k} = h_{bk}^{H}x_{k} + \sum_{l \in \mathcal{K}, l \neq k} h_{lk}^{H}x_{l} + v_{k}, k \in \mathcal{K},$$

where $v_{k}$ represents the additive white Gaussian noise (AWGN) with variance $\sigma_{w}^{2}$.
where the superscript $H$ denotes the conjugate transpose, $h_k^H x_k$ is the desired signal for MT $k$, $\sum_{i \in \mathcal{K}, i \neq k} h_k^H x_i$ is the inter-user interference from the same cluster, and $\eta_k$ denotes the background additive white Gaussian noise (AWGN) at MT $k$, which may also include the downlink interference from other BSs outside this cluster. We assume that $\eta_k$’s are independent circularly symmetric complex Gaussian (CSCG) random variables each with zero mean and variance $\sigma_k^2$. Thus, the signal-to-interference-plus-noise-ratio (SINR) at MT $k$ can be expressed as
\[
\text{SINR}_k(\{w_k\}) = \frac{|h_k^H w_k|^2}{\sum_{i \in \mathcal{K}, i \neq k} |h_k^H w_i|^2 + \sigma_k^2}, \quad k \in \mathcal{K}.
\]
The transmit power at each BS $i$, i.e., $P_{t,i}$ in (3), can be expressed as
\[
P_{t,i} = \sum_{k \in \mathcal{K}} w_k^H B_i w_k, \forall i \in \mathcal{N},
\]
where $B_i \triangleq \text{Diag}(0, \ldots, 0, 1, \ldots, 1, 0, \ldots, 0)$, with
\[
\text{Diag}(a) \text{ denoting a diagonal matrix with the diagonal elements given in vector } a.
\]

### C. Problem Formulation

We aim to jointly optimize the $N$ BSs’ purchased/sold energy from/to the grid, $\{G_{b,i}\}$ and $\{G_{s,i}\}$, and their cooperative transmit beamforming vectors, $\{w_k\}$, so as to minimize the total energy cost of all $N$ BSs, i.e., $\sum_{i \in \mathcal{N}} C_i$ with $C_i$ given in (1), subject to each MT’s QoS constraint that is specified by a minimum SINR requirement $\gamma_k$ for MT $k \in \mathcal{K}$. Specifically, we formulate the joint energy trading and beamforming optimization problem as

\[
\begin{align*}
\text{(P1)}: & \quad \min_{\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}} \sum_{i \in \mathcal{N}} (\alpha_{b,i} G_{b,i} - \alpha_{s,i} G_{s,i}) \\
& \quad \text{s.t. } \text{SINR}_k(\{w_k\}) \geq \gamma_k, \forall k \in \mathcal{K} \\
& \quad \quad \sum_{k \in \mathcal{K}} w_k^H B_i w_k + P_{t,i} \leq E_i + G_{b,i} - G_{s,i}, \forall i \in \mathcal{N} \\
& \quad \quad G_{b,i} \geq 0, G_{s,i} \geq 0, \forall i \in \mathcal{N},
\end{align*}
\]

where (6) denotes the set of QoS constraints for $K$ MTs, and (7) specifies the power constraints at $N$ BSs by combining (3) and (4). Notice that problem (P1) is in general non-convex due to the non-convex QoS constraints in (6).

Before solving (P1), we first check its feasibility. Since each BS can potentially draw infinitely large amount of energy from the grid to increase its transmit power, checking the feasibility of (P1) is equivalent to solving the following problem:

\[
\begin{align*}
\text{find } & \quad \{w_k\} \\
& \quad \text{s.t. } \text{SINR}_k(\{w_k\}) \geq \gamma_k, \forall k \in \mathcal{K}.
\end{align*}
\]

Problem (9) has been solved by the standard convex optimization techniques via reformulating it as a second-order cone program (SOCP) [1] or by the uplink-downlink duality based fixed point iteration algorithm [13]. In the rest of this paper, we assume that (P1) is feasible.

### III. Optimal Solution

In this section, we present the optimal solution to problem (P1).

#### A. Convex Reformulation of (P1)

First, we show that (P1) can be recast as a convex optimization problem. It is observed that any phase rotation of $\{w_k\}$ does not change the SINR in (6) or the power consumption in (7). Without loss of generality, we can choose $\{w_k\}$ such that $h_k^H w_k$ is real and $h_k^H w_k \geq 0, \forall k \in \mathcal{K}$. In this case, by denoting $W = [w_1, \ldots, w_K]$, we can reformulate (P1) as

\[
\begin{align*}
\left(\text{P1-Ref}\right): & \quad \min_{\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}} \sum_{i \in \mathcal{N}} (\alpha_{b,i} G_{b,i} - \alpha_{s,i} G_{s,i}) \\
& \quad \text{s.t. } |h_k^H W|^2 \leq 1 + \frac{1}{\gamma_k} h_k^H w_k, \forall k \in \mathcal{K} (10)
\end{align*}
\]

and (8), where $|| \cdot ||$ denotes the Euclidean norm of a complex vector. Since the constraints in (10) specify a set of second-order cones and thus are convex [6], it is evident that problem (P1-Ref) is convex, given that its objective and other constraints are all convex. Accordingly, we can solve problem (P1-Ref) by standard convex optimization techniques such as the interior point method [5].

#### B. An Efficient Algorithm for Solving (P1)

In order to provide more insights, we propose an alternative algorithm for solving problem (P1) efficiently by applying the Lagrange dual method [6] together with the uplink-downlink duality technique [7].

Let the dual variable associated with the $i$th power constraint in (7) be denoted by $\mu_i \geq 0, i \in \mathcal{N}$. Then we can express the partial Lagrangian of (P1) as

\[
\text{L}(\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\}) = \sum_{k \in \mathcal{K}} w_k^H B_k w_k + \sum_{i \in \mathcal{N}} (\alpha_{b,i} - \mu_i) G_{b,i} \\
+ \sum_{i \in \mathcal{N}} (\mu_i - \alpha_{s,i}) G_{s,i} + \sum_{i \in \mathcal{N}} (P_{t,i} - E_i) \mu_i,
\]

where $B_k \triangleq \sum_{i \in \mathcal{N}} \mu_i B_i$. Accordingly, the dual function is given by

\[
g(\{\mu_i\}) = \min_{\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\}} \text{L}(\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\})
\]

s.t. \quad \text{SINR}_k(\{w_k\}) \geq \gamma_k, \forall k \in \mathcal{K},

and thus the dual problem is expressed as

\[
\text{(D1)}: \quad \max_{\{\mu_i \geq 0\}} g(\{\mu_i\}).
\]

Since (P1) itself is not convex, only weak duality in general holds between (P1) and its dual problem (D1), that is, the optimal value achieved by (D1) is generally a lower bound on that by (P1) [9]. However, due to the fact that (P1) can be recast into a convex form in (P1-Ref), it can be shown that strong duality indeed holds between (P1) and (D1), as stated in the following proposition.

**Proposition 3.1:** The optimal value achieved by (D1) is equal to that by (P1).

**Proof:** See Appendix [A]

According to Proposition 3.1, we can solve (P1) by equivalently solving (D1). In the following, we first solve the problem in (12) for obtaining $g(\{\mu_i\})$ under any given $\{\mu_i\}$.
satisfying \( \mu_i \geq 0, \forall i \in \mathcal{N} \), and then minimize \( g(\{\mu_i\}) \) over \( \{\mu_i\} \).

1. Solve Problem (12) for Obtaining \( g(\{\mu_i\}) \): First, we have the following lemma.

**Lemma 3.1:** In order for \( g(\{\mu_i\}) \) to be bounded from below, i.e., \( g(\{\mu_i\}) > -\infty \), it must hold that
\[ \alpha_{s,i} \leq \mu_i \leq \alpha_{b,i}, \forall i \in \mathcal{N}. \] (14)

**Proof:** See Appendix B.

According to Lemma 3.1, we only need to derive \( g(\{\mu_i\}) \) for given \( \{\mu_i\} \) satisfying \( 0 < \alpha_{s,i} \leq \mu_i \leq \alpha_{b,i}, \forall i \in \mathcal{N} \). In this case, we have \( B_\mu > 0 \), i.e., \( B_\mu \) is positive definite. Furthermore, we observe that the problem in (12) can be decomposed into the following 2\( N + 1 \) subproblems by dropping the irrelevent term \( \sum_{i \in \mathcal{N}}(P_{k,i} - E_i)\mu_i \):
\[ \begin{align*}
\min_{\{\mu_i\}} & \quad \sum_{k \in \mathcal{K}} w_k^H B_\mu w_k \\
\text{s.t.} & \quad \text{SINR}_k(\{w_k\}) \geq \gamma_k, \forall k \in \mathcal{K}, \quad (15) \\
\min_{G_{s,i} \geq 0} & \quad (\alpha_{b,i} - \mu_i)G_{s,i}, \quad \forall i \in \mathcal{N}, \quad (16) \\
\min_{G_{s,i} \geq 0} & \quad (\mu_i - \alpha_{s,i})G_{s,i}, \quad \forall i \in \mathcal{N}, \quad (17)
\end{align*} \]
where (16) and (17) each corresponds to \( N \) subproblems (one for each BS \( i \)). For the subproblems in (16) and (17), it is easy to show that the optimal solutions are given by
\[ G_{s,i}^* = \gamma_{s,i}^*, \forall i \in \mathcal{N}. \] (18)
Therefore, it only remains to solve problem (15) with \( B_\mu > 0 \) for obtaining \( g(\{\mu_i\}) \). To this end, we exploit the uplink-downlink duality as follows.

Problem (15) can be viewed as a transmit beamforming problem for a multiple-input single-output broadcast channel (MISO-BC), as shown in the left sub-figure of Fig. 2 with the goal of minimizing the weighted sum-power \( \sum_{k \in \mathcal{K}} w_k^H B_\mu w_k \) at the transmitter subject to a set of SINR constraints \( \{\gamma_k\} \). For the MISO-BC, its single-input multiple-output multiple-access channel (SIMO-MAC) is shown in the right sub-figure of Fig. 2 by conjugating and transposing the channel vectors, where \( K \) single-antenna transmitters send independent information to one common receiver with \( MN \) antennas. For transmitter \( k \in \mathcal{K} \), let \( \lambda_k \) be its transmit power, \( \sigma_k^2 \) denote its transmitted information signal with zero mean and unit variance, and \( h_k \) be its channel vector to the receiver in the dual SIMO-MAC. Then the received signal is expressed as \( y = \sum_{k \in \mathcal{K}} h_k \sqrt{\sigma_k^2} s_k + \hat{v} \), where \( \hat{v} \) is a CSCG random vector with mean zero and covariance matrix \( B_\mu \) denoting the equivalent noise vector at the receiver. By applying receive beamforming vector \( w_k \)'s, the SINRs of different users in the dual SIMO-MAC are then given by
\[ \text{SINR}_k^*(\{w_k\}) = \frac{\lambda_k |h_k^H w_k|^2}{\sum_{l \in \mathcal{K}, l \neq k} \lambda_l |h_l^H w_k|^2 + \sum_{\ell} w_k^H B_\mu w_{\ell}}, \forall k \in \mathcal{K}. \] (19)

Note that if \( \mu_i = \alpha_{s,i} \) or \( \mu_i = \alpha_{b,i} \) for any \( i \in \mathcal{N} \), then the corresponding optimal solution of \( G_{s,i}^* \) or \( G_{s,i}^* \) in (18) is generally not unique and can take any nonnegative value. For convenience, we let \( G_{s,i}^* = 0 \) or \( G_{s,i}^* = 0 \) in this case for solving problem (16) or (17).

The design objective for the dual SIMO-MAC is to minimize the weighted sum transmit power \( \sum_{k \in \mathcal{K}} \lambda_k \sigma_k^2 \) by jointly optimizing the power allocation \( \{\lambda_k\} \) and receive beamforming vectors \( \{w_k\} \) subject to the same set of SINR constraints \( \{\gamma_k\} \) as in the original MISO-BC given by (15). We thus formulate the dual uplink problem as
\[ \min_{\{w_k\},(\lambda_k \geq 0)} \sum_{k \in \mathcal{K}} \lambda_k \sigma_k^2 \]
\[ \text{s.t.} \quad \text{SINR}_k^*(\{w_k\},\{\lambda_k\}) \geq \gamma_k, \forall k \in \mathcal{K}. \] (20)

With \( B_\mu > 0 \), it has been shown in (7) that problems (15) and (20) are equivalent. Thus, we can solve the downlink problem (15) by first solving the uplink problem (20) and then mapping its solution to that of problem (15), shown as follows.

First, consider the uplink problem (20). Since it can be shown that the optimal solution of (20) is always achieved when all the SINR constraints are met with equality (7), it follows that the optimal uplink transmit power \( \lambda_k^* \) must be a fixed point solution of the following equations, and thus can be found via iterative function evaluation (12).
\[ \lambda_k^* = \frac{1}{1 + \frac{1}{\gamma_k}} h_k^H \left( \sum_{l \in \mathcal{K}} \lambda_l h_l h_l^H + B_\mu \right)^{-1} h_k, \forall k \in \mathcal{K}. \] (21)

where the superscript ‘\(-1\)’ denotes the inverse of a square matrix. With \( \lambda_k^* \) at hand, the optimal receive beamforming vector \( \{w_k^*\} \) can then be obtained based on the minimum-mean-squared-error (MMSE) principle as
\[ w_k^* = \left( \sum_{l \in \mathcal{K}} \lambda_l h_l h_l^H + B_\mu \right)^{-1} h_k, \forall k \in \mathcal{K}. \] (22)

After obtaining the optimal solution of \( \{w_k^*\} \) and \( \lambda_k^* \) for the uplink problem (20), we then map the solution to \( \{w_k^*\} \) for the downlink problem (15). As shown in (7), \( \{w_k^*\} \) and \( \{w_k^*\} \) are identical up to a certain scaling factor. Using this argument together with the fact that the optimal solution of (15) is also attained with all the SINR constraints being tight similarly to problem (20), it follows that \( \{w_k^*\} \) can be obtained as \( w_k^* = \sqrt{\sigma_k^2} w_k^*, \forall k \in \mathcal{K}, \) with \( p^* = [p_1^*, \ldots, p_K^*]^T \) given by
\[ p^* = \left( I - D(\{w_k^*, \gamma_k\}) \right)^{-1} u(\{w_k^*, \gamma_k\}), \] (23)
where \( D_{kl}(\{w_k, \gamma_k\}) = \begin{cases} 0, & k = l \\ \frac{\gamma_k h_k^H w_k^*}{|h_k^* w_k^*|^2}, & k \neq l \end{cases} \) and
\[ u(\{w_k, \gamma_k\}) = \frac{\gamma_k \sigma_k^2}{|h_k^* w_k^*|^2}, \ldots, \frac{\gamma_k \sigma_k^2}{|h_K^* w_K^*|^2} \]. Here, \([D]_{kl}\)
denotes the element in the $k$th row and $l$th column of $D$.

2) Minimize $g(\{\mu_i\})$ over $\{\mu_i\}$: Up to now, we have obtained the optimal solution of $\{w^*_i\}$, $\{G^*_{b,i}\}$, and $\{G^*_{s,i}\}$ to the problem in (12) with given $\{\mu_i\}$. Accordingly, the dual function $g(\{\mu_i\})$ has been obtained. Next, we solve problem (D1) by minimizing $g(\{\mu_i\})$ over $\{\mu_i\}$. Since $g(\{\mu_i\})$ is convex but not necessarily differentiable, we can employ the ellipsoid method [14] to obtain the optimal $\{\mu^*_i\}$ for (D1) by using the fact that the subgradient of $g(\{\mu_i\})$ at given $\mu_i$ can be shown to be $\sum_{k \in K} w^{*H}_k B_i w^*_k + P_{c,i} - E_i - G^*_{b,i} + G^*_{s,i} = \sum_{k \in K} w^{*H}_k B_i w^*_k + P_{c,i} - E_i, \forall i \in N$.

With the obtained $\{\mu^*_i\}$, the corresponding $\{w^*_i\}$ becomes the optimal transmit beamforming vectors for (P1), denoted by $\{w^*_i\}$. However, the solutions of $\{G^*_{b,i}\}$ and $\{G^*_{s,i}\}$ given by (18) in general may not be the optimal solution to (P1), since they are not unique if $\alpha_{b,i} - \mu^*_i = 0$ or $\mu^*_i - \alpha_{s,i} = 0$, for any $i \in N$. Nevertheless, it can be easily checked that the optimal solution to (P1) is achieved when the constraints in (12) are all met with equality. As a result, the optimal solution of $\{G^*_{b,i}\}$ and $\{G^*_{s,i}\}$ for (P1) can be obtained as

$$G^*_{b,i} = \left( \sum_{k \in K} w^{*H}_k B_i w^*_k + P_{c,i} - E_i \right)^+, \quad (24)$$

$$G^*_{s,i} = \left( E_i - \sum_{k \in K} w^{*H}_k B_i w^*_k - P_{c,i} \right)^+, \forall i \in N, \quad (25)$$

with $(x)^+ = \max(0,x)$. This result is intuitive, since if the amount of harvested energy by BS $i, E_i$, is smaller (or larger) than that of its consumed energy, $\sum_{k \in K} w^{*H}_k B_i w^*_k + P_{c,i}$, then BS $i$ should purchase the insufficient energy (or sell the excess energy) from (or to) the grid.

To summarize, our proposed algorithm to solve (P1) is given in Table I as Algorithm 1.

For comparison, we also consider the following baseline scheme which separately designs cooperative communication and energy trading at BSs. First, similar to [12], [13], the sum-power of $N$ BSs is minimized subject to the QoS constraints given in (9), i.e.,

$$(P2): \min_{\{w_k\}} \left\{ \sum_{k \in K} \|w_k\|^2 \right\}$$

s.t. $\text{SINR}_k(\{w_k\}) \geq \gamma_k, \forall k \in K$.

Then, by letting $\{w^{*\alpha}_{k}\}$ denote the optimal beamforming solution of (P2), the energy trading solutions with the grid at each of the $N$ BSs are independently set as $G^*_{b,i} = \left( \sum_{k \in K} w^{*H}_{k\alpha} B_i w^{*\alpha}_k + P_{c,i} - E_i \right)^+$ and $G^*_{s,i} = \left( E_i - \sum_{k \in K} w^{*H}_{k\alpha} B_i w^{*\alpha}_k - P_{c,i} \right)^+, \forall i \in N$. Interestingly, we show that the baseline scheme yields the same optimal beamforming and energy trading solution as (P1) for the special case of equal energy buying and selling prices at all BSs, i.e., $\alpha_{b,i} = \alpha_{s,i} \neq 0, \forall i \in N$. In this case, we have $\mu^*_i = \alpha, \forall i \in N$, and accordingly $B_{\mu_i} = \sum_{i \in N} \mu^*_i B_i = \alpha I$ for (P1). As a result, the subproblem of (P1) in [15] becomes equivalent to (P2). Therefore, their beamforming (and thus energy trading) solutions become identical. However, for the general case of $\alpha_{b,i} \neq \alpha_{s,i}$ for any $i \in N$, the baseline scheme yields only a suboptimal solution for (P1), as will be shown by simulation results next.

IV. NUMERICAL RESULTS

In this section, we provide simulation results to evaluate the performance of our proposed scheme with joint energy trading and communication cooperation by solving (P1), as compared to the baseline scheme with separate communication cooperation and energy trading via solving (P2). We consider a practical three-BS cluster (with $N = 3$), where the cells are hexagonal with the inter-BS distance of one kilometer, the number of transmit antennas at each BS is $M = 4$, and the total number of MTs is $K = 8$. We assume that BS 1 and BS 2 are deployed with solar and wind generators, respectively, while BS 3 has both of them deployed. Then based on a real-world solar and wind energy production data, we model the energy harvesting rates at the three BSs as shown in Fig. 3, where the harvested energy at each BS has been averaged over 15 minutes, and thus there are 384 energy harvesting rate samples for each BS over 96 hours (i.e., four days). For each renewable energy sample, we apply the same set of rate samples for each BS over 96 hours (i.e., four days).

| TABLE I |
| --- |
| ALGORITHM FOR SOLVING PROBLEM (P1) |
| 1) Initialize $\{\mu_i\}$ with $\alpha_{s,i} \leq \mu_i \leq \alpha_{b,i}, \forall i \in N$. |
| 2) Repeat: |

- a) Compute $\{\lambda^*_i\}$ as a fixed point solution of (21) by iterative function evaluation (19), and compute the uplink receive beamforming vectors $\{w^*_i\}$ by (22).

- b) Compute the downlink beamforming vectors as $w^*_i = \sqrt{P_i} w^*_k, \forall k \in K$, with $\{\mu_i\}$ given by (23).

- c) Compute the subgradient of $g(\{\mu_i\})$ associated with $\mu_i$ as $\sum_{k \in K} w^{*H}_k B_i w^*_k - E_i + P_{c,i}, \forall i \in N$, then update $\{\mu_i\}$ accordingly based on the ellipsoid method [14], subject to $\alpha_{s,i} \leq \mu_i \leq \alpha_{b,i}, \forall i \in N$.

3) Until $\{\mu_i\}$ all converge within a prescribed accuracy.

4) Set $w^*_i = w^*_k, \forall k \in K$.

5) Compute $\{G^*_{b,i}\}$ and $\{G^*_{s,i}\}$ given by (24) and (25).

This result is intuitive, since if the background noise and the QoS requirement at each MT receiver are $\sigma^2 = -85$ dBm and $\gamma_k = 10$ dB, $\forall k \in K$, respectively, while the PA efficiency and the non-transmission constant power at each BS are $\eta = 0.1$ and $P_{c,i} = 500$ Watt (W), $\forall i \in N$, respectively. We consider the prices for buying (selling) energy from (to) the grid as $\alpha_{b,i} = 1$KiloWatt (kW) ($\alpha_{s,i} = 0.1$/kW), $\forall i \in N$, where the price unit is normalized without loss of generality.

Fig. 3 shows the average power consumption at each of the three BSs over time, together with its harvested energy profile. For the baseline scheme, it is observed that the average power consumption at each BS remains constant over time, regardless of the fluctuations in energy harvesting rates at each BS. This is because the baseline scheme solves the sum-power minimization problem (P2) to obtain the transmit beamforming solution by ignoring the two-way energy trading prices and the energy harvesting rates at all the BSs; as a result, the average power consumption for each BS is constant. By contrast, the proposed solution to (P1) exploits the two-way energy trading profit; consequently, the harvested energy at each cell is used efficiently for both communication and energy storage.

See [http://www.elia.be/en/grid-data/power-generation/](http://www.elia.be/en/grid-data/power-generation/)
power consumption at each BS is constant for this purposely designed setup with fixed number of users and the same set of wireless channels over the time. In contrast, for the proposed optimal solution, the resulting average power consumption at each BS is observed to vary following a similar pattern as the corresponding energy harvesting rates. For example, during hours 0-9, BS 1 with large locally generated wind energy increases its transmission power and accordingly decreases the excess energy sold to the grid, while BS 2 and BS 3 with zero/smaller locally generated solar energy reduce their transmission power that need to be purchased from the grid, in order to minimize the total energy cost of the three BSs, given that $\alpha_{s,i} < \alpha_{b,i}, \forall i \in N$.

Fig. 4 shows the total energy cost of the three BSs over time based on the results in Fig. 3. It is observed that the proposed optimal solution reduces the total energy cost as compared to the baseline scheme at all time, which is expected since the baseline scheme in this case obtains only a suboptimal solution for (P1). The energy cost reduction is also observed to be more substantial when the energy harvesting rates at different BSs are more unevenly distributed, e.g., during hours 0-9 and 20-30. On average, a notable 21.8% total energy cost reduction over the entire period of four days is achieved.

V. CONCLUSION

In this paper, we proposed a new cooperative energy trading approach for the downlink CoMP transmission powered by smart grids to reduce the energy cost of cellular systems. We minimize the total energy cost at the BSs in one CoMP cluster subject to the QoS constraints of MTs, by jointly optimizing the BSs’ two-way energy trading with the grid and their cooperative transmit beamforming. We propose an efficient algorithm for this problem via applying techniques from convex optimization and uplink-downlink duality. We show that interestingly, the conventional approach of minimizing the sum-power consumption of BSs is no more optimal when two-way energy trading with the grid is considered, while a joint energy trading and communication cooperation optimization is necessary to achieve the minimal energy cost for the system.

APPENDIX

A. Proof of Proposition 3.1

Since (P1) can be recast as the equivalent form of (P1-Ref), it follows that $v_{(P1)} = v_{(P1-Ref)}$ with $v_{(P1)}$ and $v_{(P1-Ref)}$ denoting the optimal values of (P1) and (P1-Ref), respectively. Let $v_{(D1)}$ denote the optimal value of (P1). We then prove Proposition 3.1 by showing that $v_{(D1)} = v_{(P1-Ref)}$.

Let the dual variables associated with the power constraints of (P1-Ref) be denoted by $\mu_i \geq 0, i \in N$. Then the partial Lagrangian of problem (P1-Ref) can also be expressed as $L (\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\})$ in (11), and accordingly its dual function is given by

$$g_{Ref}(\{\mu_i\}) = \min_{\{w_k\}: \{G_{b,i}\} \geq 0, \{G_{s,i}\} \geq 0} L (\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\})$$

s.t. $h_k^H \sigma \leq \sqrt{1 + \frac{1}{\gamma_k}} h_k^H w_k, \forall k \in K$.

The dual problem of (P1-Ref) is thus expressed as

$$(D1-Ref) : \max_{\{\mu_i\} \geq 0} g_{Ref}(\{\mu_i\})$$

Since (P1-Ref) is convex and satisfies the Slater’s condition, we have $v_{(P1-Ref)} = v_{(D1-Ref)}$ with $v_{(D1-Ref)}$ denoting the optimal value of (D1-Ref). Meanwhile, it is evident that $g_{Ref}(\{\mu_i\}) = g(\{\mu_i\})$ holds for any given $\{\mu_i\}$ due to the equivalent relationship between (6) and (10). As a result, we can have $v_{(D1)} = v_{(D1-Ref)} = v_{(P1-Ref)}$. Combining this argument with $v_{(P1)} = v_{(P1-Ref)}$, it follows that $v_{(D1)} = v_{(P1)}$. Therefore, Proposition 3.1 is finally proved.

B. Proof of Lemma 3.1

First, we assume that $\mu_i < \alpha_{s,i}$ for any $i \in N$. In this case, it follows that $L (\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\}) \to -\infty$ if $G_{s,i} \to \infty$. That is, $g(\{\mu_i\})$ is unbounded from below. As a
result, $\mu_i < \alpha_{s,i}$ cannot be true in order for $g(\{\mu_i\})$ to be bounded from below. It thus follows that $\mu_i \geq \alpha_{s,i}, \forall i \in N$.

Next, we assume that $\mu_i > \alpha_{b,i}$ for any $i \in N$. In this case, it can be shown that $L(\{w_k\}, \{G_{b,i}\}, \{G_{s,i}\}, \{\mu_i\}) \to -\infty$ holds if $G_{b,i} \to \infty$. That is, $g(\{\mu_i\})$ is unbounded from below. As a result, $\mu_i > \alpha_{b,i}$ cannot be true in order for $g(\{\mu_i\})$ to be bounded from below. It thus follows that $\mu_i \leq \alpha_{b,i}, \forall i \in N$.

By combining the two cases, Lemma 3.1 follows immediately.

REFERENCES

[1] D. Gesbert, S. Hanly, H. Huang, S. Shamai, O. Simeone, and W. Yu, “Multi-cell MIMO cooperative networks: A new look at interference,” IEEE J. Sel. Areas Commun., vol. 28, no. 9, pp. 1380-1408, Dec. 2010.

[2] Huawei, “Mobile networks go green,” available online at http://www.huawei.com/en/about-huawei/publications/communicate/hw-082734.htm

[3] S. Chen, N. B. Shroff, and P. Sinha, “Energy trading in the smart grid: from end-user’s perspective,” in Proc. Asilomar Conference on Signals, Systems & Computers, Nov. 2013.

[4] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, “A game-theoretic approach to energy trading in the smart grid,” to appear in IEEE Trans. Smart Grid.

[5] J. Leitão, T. J. Lim, and S. Sun, “Online energy management strategies for base stations powered by the smart grid,” in Proc. 2013 IEEE SmartGridComm, pp. 199-204, Oct. 2013.

[6] S. Boyd and L. Vandenberghe, Convex Optimization, Cambridge University Press, 2004.

[7] W. Yu and T. Lan, “Transmitter optimization for the multi-antenna downlink with per-antenna power constraints,” IEEE Trans. Sig. Process., vol. 55, no. 6, pp. 2646-2660, Jun. 2007.

[8] Y. Bu, F. R. Yu, Y. Cai, and X. P. Liu, “When the smart grid meets energy-efficient communications: Green wireless cellular networks powered by the smart grid,” IEEE Trans. Wireless Commun., vol. 11, no. 8, pp. 3014-3024, Aug. 2012.

[9] Y. K. Chia, S. Sun, and R. Zhang, “Energy cooperation in cellular networks with renewable powered base stations,” in Proc. 2013 IEEE WCNC, pp. 2542-2547, Apr. 2013.

[10] Y. Guo, J. Xu, L. Duan, and R. Zhang, “Optimal energy and spectrum sharing for cooperative cellular systems,” to appear in Proc. 2014 IEEE ICC, available online at [arXiv:1312.1756].

[11] J. Xu, Y. Guo, and R. Zhang, “CoMP meets energy harvesting: A new communication and energy cooperation paradigm,” in Proc. 2013 IEEE Globecom, pp. 2430-2435, Dec. 2013.

[12] A. Wiesel, Y. C. Eldar, and S. Shamai, “Linear precoding via conic optimization for fixed MIMO receivers,” IEEE Trans. Sig. Process., vol. 54, no. 1, pp. 161-176, Jan. 2006.

[13] M. Bengtsson and B. Ottersten, “Optimal and suboptimal transmit beamforming,” in Handbook of Antennas in Wireless Communications, L. C. Godara, Ed. CRC Press, 2002.

[14] S. Boyd, “Convex optimization II,” Stanford University. Available online at [http://www.stanford.edu/class/ee364b/lectures.html]