AN ONLINE THROUGHPUT MAXIMIZATION ALGORITHM FOR GREEN COORDINATED MULTI-POINT SYSTEMS

Yanjie Dong[1]*, Haijun Zhang*[2]*, Jianqiang Li*[1]*, F. Richard Yu*[3]*, Song Guo*[4]*, Victor C. M. Leung*[1,5]

[1]Shenzhen University, [2]University of Science and Technology Beijing, [3]Carleton University,
[4]The Hong Kong Polytechnic University, [5]The University of British Columbia

ABSTRACT

Wireless systems are upgraded to use green energy (e.g., solar, wind, and tide energy) such that the greenhouse gas emission can be neutralized. This work incorporates the on-grid energy into a *green* coordinated multi-point (CoMP) system to handle the volatile arrival of green energy. In the green CoMP, the long-term weighted throughput maximization problem is investigated by expecting a non-positive consumption of the long-term on-grid energy. Motivated by the capacity-achieving property and simple implementation, an online zero-forcing dirty paper precoder is proposed to update the precoding matrices by combining statistical learning with the Lyapunov learning. A tradeoff relation is theoretically established to show that the long-term weighted throughput approaches the $\mathcal{O}(V)$-neighbor of optimal value while the long-term consumed on-grid energy increases at a rate of $\mathcal{O}(\log^2(V)/\sqrt{V})$, where V is an introduced control parameter. Numerical results are used to verify the performance of the online zero-forcing dirty paper precoder.

***Index Terms*—** Coordinated multi-point transmission, green communications, online learning algorithm.

1. INTRODUCTION

In a cloud radio access network, the deployed remote radio heads (RRHs) can jointly preprocess the information of user equipments (UEs) to further improve the communication quality of service (QoS) by forming a coordinated multi-point (CoMP) system [1, 2]. Following the roadmap of carbon neutrality, the hybrid usage of green energy and on-grid energy can be integrated into the CoMP system to reduce the energy consumption, to handle the volatile arrival of green energy, and to guarantee the QoS of UEs [3]. Three protocols can be used to incorporate green energy into a communication system, namely, harvest-use-store (HUS) protocol [4], harvest-store-use (HSU) protocol [5], and harvest-use-trade (HUT) protocol [6, 7, 8]. Compared with HUS and HSU protocols, the HUT protocol can resolve the loss and aging problems of energy storage media by exploiting the two-way energy trading property of smart grid [6, 7, 8]. Therefore, the HUT protocol is applied to the investigated green CoMP system of this work. Based on the HUT protocol, X. Zhang *et al.* [6] investigated the joint beamforming and renewable utilization problem in a CoMP system. However, the quantitative relationship was not revealed in [6] for the long-term on-grid energy consumption and the long-term system throughput.

Since the seminal work [9], Lyapunov learning has been widely used in resource allocation problems of communication systems [10, 11]. For example, by using a control parameter V, the long-term on-grid energy expenditure can approach the optimal value at a rate of $\mathcal{O}(V)$ when the end-to-end delay of UEs increases at a rate of $\mathcal{O}(1/V)$ for single-cell [7] and multi-cell communication systems [8]. However, recent research works reported several tradeoff bounds that are more efficient than the vanilla Lyapunov learning [12, 13, 14]. J. Liu [12] leveraged the Nesterov's momentum based algorithm to achieve the $[\mathcal{O}(V), \mathcal{O}(1/\sqrt{V})]$ tradeoff between the long-term utility and the long-term delay of UEs for a scalar-based utility maximization problem. Yet, the Nesterov's momentum based algorithm [12] can only handle the scalar-based optimization problems. By using the locally polyhedral assumption for network cost minimization problems, L. Huang *et al.* [13] developed a quadratic Lyapunov function based algorithm that can trade network utility at a rate of $\mathcal{O}(V)$ for the delay of UEs at a rate of $\mathcal{O}(\log^2(V))$. Aiming at the vector-based resource allocation problems, T. Chen *et al.* [14] relaxed the so-termed locally polyhedral assumption, and developed a learn-and-adapt algorithm that combines the statistical learning with Lyapunov learning for network cost minimization problems. Note that the learn-and-adapt algorithm requires strictly feasible assumption for the network cost minimization problems.

Different from [12, 13, 14], we investigate the long-term weighted throughput maximization problem when the long-term system energy consumption is below the arrival rate of green energy. Note that the proposed algorithm in [12] is not applicable since the variables are matrices. Besides, the proposed algorithm in [13] is also not applicable since the investigated problem does not satisfy the local polyhedral condition. Leveraging a statistical learning procedure, we apply the prestigious learn-and-adapt technique to adjust the effective price of the consumed on-grid energy, and update the zero-

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forcing dirty paper precoder (ZFDPP)[1] for RRHs based on the obtained effective price per slot. We theoretically establish that the proposed online ZFDPP algorithm can approach the optimal long-term weighted throughput at a rate of $\mathcal{O}(V)$ while the long-term on-grid energy expenditure increases at a rate of $\mathcal{O}(\log^2(V)/\sqrt{V})$, where V is an introduced control parameter. Such tradeoff bound $[\mathcal{O}(V), \mathcal{O}(\log^2(V)/\sqrt{V})]$ is superior to the tradeoff bound $[\mathcal{O}(V), \mathcal{O}(1/V)]$ of Lyapunov learning [7, 8, 9, 16]. Numerical results are used to verify the effectiveness of the proposed online ZFDPP algorithm.

2. SYSTEM MODEL AND PROBLEM DESCRIPTION

Consider downlink transmission of the green CoMP system, which consists of a central baseband processing unit (BPU), M RRHs, and N UEs. Each RRH m is equipped with $L_{m,\text{Tx}}$ transmit antennas, and each UE n is equipped with $L_{n,\text{Rx}}$ receive antennas. The RRHs are distributed in the same coverage region, and are connected to the BPU via interference-free optical links. The RRHs communicate with the N users through the time-division duplex mode such that the RRHs can obtain the perfect CSI by exploiting the channel reciprocity in the time-division duplex mode [17].

Let each entry of channel-coefficient matrix between RRH m and UE n (link (m,n)) per slot k, $H_{m,n,k} \in \mathbb{C}^{L_{m,\text{Tx}} \times L_{n,\text{Rx}}}$, satisfy circularly symmetric complex Gaussian (CSCG) distribution as $\mathcal{CN}(0, \omega_{m,n}^{-1}\sigma_n^{-2})$ where $\omega_{m,n}$ is the pathloss for link (m,n), and σ_n^2 is the noise power. The received signal at UE n per slot k is denoted by $\boldsymbol{y}_{n,k} = \boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{n,k}\boldsymbol{s}_{n,k} + \sum_{i>n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k}\boldsymbol{s}_{i,k} + \sum_{i<n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k}\boldsymbol{s}_{i,k} + \boldsymbol{z}_{n,k}$ where $\boldsymbol{H}_{n,k} := [H_{1,n,k}^{\text{H}}, H_{2,n,k}^{\text{H}}, \ldots, H_{M,n,k}^{\text{H}}]^{\text{H}} \in \mathbb{C}^{L_{\text{Tx}} \times L_{n,\text{Rx}}}$ is the compact channel-coefficient matrix for UE n per slot k with $L_{\text{Tx}} = \sum_{m=1}^{M} L_{m,\text{Tx}}$; the matrix $\boldsymbol{W}_{n,k} := [W_{1,n,k}^{\text{H}}, W_{2,n,k}^{\text{H}}, \ldots, W_{M,n,k}^{\text{H}}]^{\text{H}} \in \mathbb{C}^{L_{\text{Tx}} \times \ell_n}$ is the precoder of UE n per slot k with $W_{m,n,k}$ denoting the precoder for link (m,n) per slot k with ℓ_n information streams, $\ell_n \leq \min\{L_{\text{Tx}}, L_{n,\text{Rx}}\}$; the signaling $\boldsymbol{s}_{n,k} \in \mathbb{C}^{\ell_n}$ is chosen from Gaussian random codebook with mean zero and covariance $\mathbb{E}[\boldsymbol{s}_{n,k}\boldsymbol{s}_{n,k}^{\text{H}}] = \boldsymbol{I}_{\ell_n}$; and, $\boldsymbol{z}_{n,k}$ is the additive white Gaussian noise with mean zero and covariance $\boldsymbol{I}_{L_{n,\text{Rx}}}$.

Using successive encoding with Gaussian codebook [18, 19, 20], the interference term $\sum_{i<n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k}$ can be canceled. The weighted throughput and the consumed energy per slot k are respectively denoted by

$$C([\boldsymbol{W}_{n,k}]_{n=1}^{N}) = \sum_{n=1}^{N}\eta_n \log\frac{|\boldsymbol{I}_{L_{n,\text{Rx}}} + \sum_{i\geq n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k}\boldsymbol{W}_{i,k}^{\text{H}}\boldsymbol{H}_{n,k}|}{|\boldsymbol{I}_{L_{n,\text{Rx}}} + \sum_{i>n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k}\boldsymbol{W}_{i,k}^{\text{H}}\boldsymbol{H}_{n,k}|} \quad (1)$$

and $P([\boldsymbol{W}_{n,k}]_{n=1}^{N}) = \sum_{n=1}^{N}\text{Tr}(\boldsymbol{W}_{n,k}\boldsymbol{W}_{n,k}^{\text{H}})$, where $\eta_n > 0$ denotes the weight for UE n.

We consider that the number of transmit antennas satisfies $\sum_{m=1}^{M} L_{m,\text{Tx}} \geq \sum_{n=1}^{N} L_{n,\text{Rx}}$ such that the zero-forcing beamforming can be performed for all UEs to cancel the remaining interference, i.e., $\sum_{i>n}\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k} = 0$. This is a mild assumption in massive MIMO scenario where the number of transmit antennas is larger than that of UEs [21]. Here, we develop the ZFDPP by using QR decomposition [22, 23, 15]. Stacking the channel matrices for all UEs and performing the QR decomposition, we obtain

$$[\boldsymbol{H}_{n,k}]_{n=1}^{N} = [\boldsymbol{Q}_{n,k}]_{n=1}^{N+1}\begin{bmatrix}\boldsymbol{R}_{1,1,k}, & \ldots, & \boldsymbol{R}_{1,N,k}\\ & \ddots & \vdots\\ & & \boldsymbol{R}_{N,N,k}\\ \boldsymbol{0}, & \ldots, & \boldsymbol{0}\end{bmatrix} \quad (2)$$

where the columns of matrix $[\boldsymbol{Q}_{n,k}]_{n=1}^{N+1}$ are orthonormal bases with $\boldsymbol{Q}_{n,k} \in \mathbb{C}^{L_{\text{Tx}} \times L_{n,\text{Rx}}}$ and $L_{N+1,\text{Rx}} = L_{\text{Tx}} - \sum_{n=1}^{N} L_{n,\text{Rx}}$ per slot k, and matrix $\boldsymbol{R}_{n,n,k} \in \mathbb{C}^{L_{n,\text{Rx}} \times L_{n,\text{Rx}}}$ is upper-triangular with $\text{rank}(\boldsymbol{R}_{n,n,k}) = L_{n,\text{Rx}}$, $n = 1, 2, \ldots, N$.

Based on (2), we obtain the effective channel-coefficient matrix of UE n per slot k as $\boldsymbol{H}_{n,k} = \sum_{i=1}^{n}\boldsymbol{Q}_{i,k}\boldsymbol{R}_{i,n,k}$. Therefore, we set the precoder of UE n per slot k as $\boldsymbol{W}_{n,k} = [\boldsymbol{Q}_{i,k}]_{i=n}^{N+1}\boldsymbol{S}_{n,k}$ with the weight matrix $\boldsymbol{S}_{n,k} \in \mathbb{C}^{\sum_{i=n}^{N+1} L_{n,\text{Rx}} \times \ell_n}$ such that the constraint $\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k} = 0$ is satisfied for $i > n$. Moreover, we have

$$\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{i,k} = \begin{cases}[\boldsymbol{R}_{n,n,k}^{\text{H}}, \boldsymbol{0}]\boldsymbol{S}_{n,k}, & i = n\\ \boldsymbol{0}, & i > n.\end{cases} \quad (3)$$

Based on (3), we obtain

$$\boldsymbol{H}_{n,k}^{\text{H}}\boldsymbol{W}_{n,k}\boldsymbol{W}_{n,k}^{\text{H}}\boldsymbol{H}_{n,k} = [\boldsymbol{R}_{n,n,k}^{\text{H}}, \boldsymbol{0}]\boldsymbol{S}_{n,k}\boldsymbol{S}_{n,k}^{\text{H}}[\boldsymbol{R}_{n,n,k}^{\text{H}}, \boldsymbol{0}]^{\text{H}} \quad (4)$$

such that the data rate of UE n is calculated as

$$\log|\boldsymbol{I} + [\boldsymbol{R}_{n,n,k}^{\text{H}}, \boldsymbol{0}]\boldsymbol{S}_{n,k}\boldsymbol{S}_{n,k}^{\text{H}}[\boldsymbol{R}_{n,n,k}^{\text{H}}, \boldsymbol{0}]^{\text{H}}|. \quad (5)$$

Note that the data rate of UE n in (5) only depends on the first $L_{n,\text{Rx}}$ rows of $\boldsymbol{S}_{n,k}$. Hence, we refine the precoder as $\boldsymbol{W}_{n,k} = \boldsymbol{Q}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}$ with $\widetilde{\boldsymbol{S}}_{n,k} \in \mathbb{C}^{L_{n,\text{Rx}} \times \ell_n}$. Define effective precoder of UE n per slot k as $\boldsymbol{\Sigma}_{n,k} := \boldsymbol{R}_{n,n,k}^{\text{H}}\widetilde{\boldsymbol{S}}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}^{\text{H}}\boldsymbol{R}_{n,n,k}$ and $\widetilde{\boldsymbol{R}}_{n,k} := \boldsymbol{R}_{n,n,k}\boldsymbol{R}_{n,n,k}^{\text{H}} \succ 0$. Substituting $\boldsymbol{\Sigma}_{n,k} := \boldsymbol{R}_{n,n,k}^{\text{H}}\widetilde{\boldsymbol{S}}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}^{\text{H}}\boldsymbol{R}_{n,n,k}$ and $\boldsymbol{W}_{n,k} = \boldsymbol{Q}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}$ into weighted throughput and consumed energy, we obtain the long-term weighted throughput (LTWT) maximization problem as

$$\max_{[\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}} \lim_{K\to\infty}\frac{1}{K}\sum_{k=1}^{K}\sum_{n=1}^{N}\eta_n\mathbb{E}\Big[\log\Big|\boldsymbol{I} + \boldsymbol{\Sigma}_{n,k}\Big|\Big] \quad (6a)$$

$$\text{s.t.} \lim_{K\to\infty}\frac{1}{K}\sum_{k=1}^{K}\mathbb{E}\Big[\sum_{n=1}^{N}\text{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k}) - P_k^{\text{ARR}}\Big] \leq 0 \quad (6b)$$

$$\sum_{n=1}^{N}\text{Tr}(\widetilde{\boldsymbol{A}}_{m,n}\boldsymbol{\Sigma}_{n,k}) \leq P^{\max}, \forall m \quad (6c)$$

$$\boldsymbol{\Sigma}_{n,k} \succeq \boldsymbol{0}, \forall n \quad (6d)$$

where $\widetilde{\boldsymbol{A}}_{m,n} := \boldsymbol{R}_{n,n,k}^{-1}\boldsymbol{Q}_{n,k}^{\text{H}}\boldsymbol{A}_m\boldsymbol{Q}_{n,k}\boldsymbol{R}_{n,n,k}^{-\text{H}}$ with

$$\boldsymbol{A}_m = \text{diag}\{\underbrace{0, \ldots, 0}_{\sum_{i=1}^{m-1} L_{i,\text{Tx}}}, \underbrace{1, \ldots, 1}_{L_{m,\text{Tx}}}, \underbrace{0, \ldots, 0}_{\sum_{i=m+1}^{M} L_{i,\text{Tx}}}\}. \quad (7)$$

[1]Compared with the capacity-achieving dirty paper coding scheme, the ZFDPP requires fewer nonlinear dirty paper coding procedures while retaining the capacity-achieving feature [15].

Since the on-grid energy is introduced as a backup source to handle the weather dependence of renewable arrival, we introduce a constraint in (6b) such that the green CoMP system: 1) only consumes the green energy in the long term; and 2) leverages the on-grid energy to guarantee the communication QoS of UEs when the green energy is in deficit. Solving the LTWT problem in (6), we obtain a set of effective precoders $[\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}$ per slot k. Performing the Cholesky decomposition to each $\boldsymbol{R}_{n,n,k}^{-\mathrm{H}}\boldsymbol{\Sigma}_{n,k}\boldsymbol{R}_{n,n,k}^{-1}$, we can obtain the expression of $\widetilde{\boldsymbol{S}}_{n,k}$ per slot k. Combining with the orthonormal bases in $[\boldsymbol{Q}_{n,k}]_{n=1}^{N+1}$, we can finally recover the set of precoders $[\boldsymbol{W}_{n,k}]_{n=1}^{N}$ per slot k via $\boldsymbol{W}_{n,k} = \boldsymbol{Q}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}$.

3. DESIGN AND ANALYSIS OF ONLINE ZERO-FORCING DIRTY PAPER PRECODER

We observe that the optimal solution to the LTWT maximization problem (6) are affected by the random complex-channel coefficient matrices $[\boldsymbol{H}_{n,k}]_{n=1,k=1}^{N,K}$ and the random arrival rate of green energy $[P_k^{\text{ARR}}]_{k=1}^{K}$. When the random sources follow stationary distributions, it has been reported that the optimal solution to (6) is a function of the random sources $[\boldsymbol{H}_{n,k}]_{n=1,k=1}^{N,K}$ and $[P_k^{\text{ARR}}]_{k=1}^{K}$ [7, 8, 14, 24]. In this work, we consider that the random sources $[\boldsymbol{H}_{n,k}]_{n=1,k=1}^{N,K}$ and $[P_k^{\text{ARR}}]_{k=1}^{K}$ follow independent and identically distributions over different slots. Hence, the problem (6) is recast into a set of per-slot optimization problems as

$$\max_{[\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}} \sum_{n=1}^{N} \eta_n \mathbb{E}\Big[\log\Big|\boldsymbol{I}+\boldsymbol{\Sigma}_{n,k}\Big|\Big] \tag{8a}$$

$$\text{s.t. } \mathbb{E}\Big[\sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k}) - P_k^{\text{ARR}}\Big] \le 0 \tag{8b}$$

$$\sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{A}}_{m,n}\boldsymbol{\Sigma}_{n,k}) \le P^{\max}, \forall m \tag{8c}$$

$$\boldsymbol{\Sigma}_{n,k} \succeq \boldsymbol{0}, \forall n. \tag{8d}$$

We leverage the Lagrange duality to derive the online ZFDPP. Denote the dual variable associated with (8b) by λ_k, and the feasible region by $\chi_k := \{\boldsymbol{\Sigma}_{n,k}|\sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{A}}_{m,n}\boldsymbol{\Sigma}_{n,k}) \le P^{\max}, \boldsymbol{\Sigma}_{n,k} \succeq \boldsymbol{0}, \forall m,n\}$.

The Lagrangian of (8) is obtained as

$$\mathcal{L}(\lambda_k, [\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}) = \mathbb{E}\Big[\sum_{n=1}^{N}\mathcal{L}_n(\lambda_k,\boldsymbol{\Sigma}_{n,k}) + \lambda_k P_k^{\text{ARR}}\Big] \tag{9}$$

where $\mathcal{L}_n(\lambda_k,\boldsymbol{\Sigma}_{n,k}) := \eta_n\log|\boldsymbol{I}+\boldsymbol{\Sigma}_{n,k}| - \lambda_k\mathrm{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k})$.

The dual function of (9) is obtained as

$$\mathcal{D}(\lambda_k) = \max_{\chi_k}\mathcal{L}(\lambda_k, [\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}) \tag{10a}$$

$$= \max_{\chi_k}\mathbb{E}\Big[\sum_{n=1}^{N}\mathcal{L}_n(\lambda_k,\boldsymbol{\Sigma}_{n,k}) + \lambda_k P_k^{\text{ARR}}\Big] \tag{10b}$$

$$= \mathbb{E}\Big[\max_{\chi_k}\sum_{n=1}^{N}\mathcal{L}_n(\lambda_k,\boldsymbol{\Sigma}_{n,k}) + \lambda_k P_k^{\text{ARR}}\Big] \tag{10c}$$

$$:= \mathbb{E}[\mathcal{D}_k(\lambda_k)] \tag{10d}$$

where equality (10c) follows from the interchangeability principle [25, Theorem 7.80].

While the adapting-and-learning technique has been successfully used in the network operational expenditure minimization problem [14, 24], we are motivated to apply the technique to the precoding process in the green CoMP system. Therefore, we need introduce two parts in the online ZFDPP, i.e., adapting procedures and statistical learning procedures. The statistical learning procedures are used to obtain the optimal dual variable λ^* for problem (8) via

$$\lambda_{k+1} = \Big[\lambda_k + \alpha_k\Big(\sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k}^{*}) - P_k^{\text{ARR}}\Big)\Big]^{+} \tag{11}$$

where α_k is the stepsize per slot k, and $[x]^{+} = \max\{x, 0\}$. Here, the solution $[\boldsymbol{\Sigma}_{n,k}^{*}]_{n=1}^{N}$ is obtained as

$$[\boldsymbol{\Sigma}_{n,k}^{*}]_{n=1}^{N} = \arg\max_{\chi^k}\sum_{n=1}^{N}\mathcal{L}_n(\lambda_k,\boldsymbol{\Sigma}_{n,k}). \tag{12}$$

Note that the solution $[\boldsymbol{\Sigma}_{n,k}^{*}]_{n=1}^{N}$ is an intermediate result and will not be allocated to UEs in the green CoMP system.

Based on (11), the effective price $\hat{\beta}_k$ of on-grid energy consumption factors in both the empirical dual variable λ_k and the accumulated on-grid energy consumption β_k as

$$\hat{\beta}_k = \lambda_k + V\beta_k - \theta \tag{13}$$

where V and θ are introduced control parameters.

Based on the effective price $\hat{\beta}_k$, the BPU can design the precoder and update the accumulated on-grid energy consumption per slot k, respectively, as

$$[\boldsymbol{\Sigma}_{n,k}^{\bullet}]_{n=1}^{N} = \arg\max_{\chi^k}\sum_{n=1}^{N}\mathcal{L}_n(\hat{\beta}_k,\boldsymbol{\Sigma}_{n,k}) \tag{14}$$

and

$$\beta_{k+1} = \Big[\beta_k + \sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k}^{\bullet}) - P_k^{\text{ARR}}\Big]^{+}. \tag{15}$$

Repeating (11)–(15), we obtain the **online ZFDPP algorithm**. Different from the classical Lyapunov learning, the design of precoders considers the accumulated on-grid energy consumption β_k and the accumulated on-grid energy consumption λ_k. By factoring in λ_k and β_k, the adapting procedures can construct the effective price of on-grid energy consumption $\hat{\beta}_k$ in (13). Then, based on the effective price $\hat{\beta}_k$, BPU outputs the effective precoders $[\boldsymbol{\Sigma}_{n,k}]_{n=1}^{N}$. Finally, the BPU obtains the precoders $[\boldsymbol{W}_{n,k}]_{n=1}^{N}$ via $\boldsymbol{W}_{n,k} = \boldsymbol{Q}_{n,k}\widetilde{\boldsymbol{S}}_{n,k}$ and the Cholesky decomposition [22] to $\boldsymbol{R}_{n,n,k}^{-\mathrm{H}}\boldsymbol{\Sigma}_{n,k}\boldsymbol{R}_{n,n,k}^{-1}$. Compared with classical Lyapunov learning, the proposed online ZFDPP algorithm only requires an extra query of the primal optimization problem, i.e., (12).

Theorem 1 *Setting $\theta = \sqrt{V}\log^2(V)$ where V is a sufficient small control parameter. When $|\sum_{n=1}^{N}\mathrm{Tr}(\widetilde{\boldsymbol{R}}_{n,k}^{-1}\boldsymbol{\Sigma}_{n,k}) - P_k^{\text{ARR}}| \le \Psi$ with $\Psi > 0$, for the the CoMP system, the long-term energy consumption and long-term throughput are, respectively, upper-bounded by*

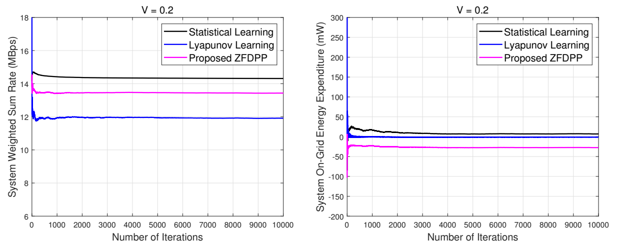

Fig. 1. Convergence of running-average weighted throughput and running-average on-grid energy consumption.

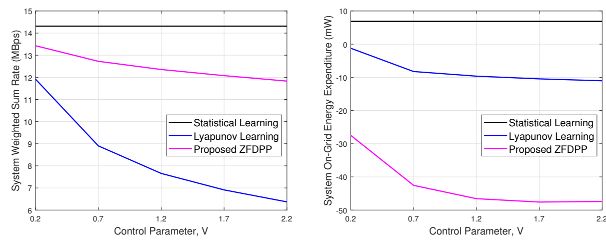

Fig. 2. Running-average weighted throughput and running-average on-grid energy vary over different values of V.

$$\lim_{K\to\infty}\frac{1}{T}\sum_{k=1}^{K}\mathbb{E}[\beta_k]\leq\mathcal{O}\Big(\frac{\log^2(V)}{\sqrt{V}}\Big) \tag{16}$$

and

$$\lim_{K\to\infty}\frac{1}{K}\sum_{k=1}^{K}\sum_{n=1}^{N}\eta_n\mathbb{E}\Big[\log\Big|\boldsymbol{I}+\boldsymbol{\Sigma}^{\bullet}_{n,k}\Big|\Big]\geq\mathcal{D}(\lambda^*)-\mathcal{O}(V). \tag{17}$$

Due to the space limitation, the proof of Theorem 1 is relegated to the extended version of this work [26]. Based on theorem 1, we conclude that the online ZFDPP algorithm converges to the $\mathcal{O}(V)$-neighbor of optimal long-term weighted throughput when increasing the long-term system on-grid energy consumption at a rate of $\mathcal{O}(\log^2(V)/\sqrt{V})$.

4. SIMULATION RESULTS AND DISCUSSIONS

We consider that the CoMP system has five RRHs and six UEs. Each RRH is equipped with four antennas, and each UE is equipped with three antennas. The pathloss exponent is set as 4, the average distance between the RRH and UE is set as 500 meters, and the system bandwidth is set as 200 KHz. The noise figure per UE is set as 5 dB, and power spectrum density of AWGN is set as -174 dBm/Hz. The stepsize α_k is set as $0.03/k$. The weights are set as $[1.0, 0.9, 0.8, 0.7, 0.6, 0.5]$. The maximum transmit power $P_k^{\max}$ is set as 200 mW. Unless otherwise clarification, the average arrival rate of green energy P_k^{ARR} is set as 150 mW.

Figure 1 shows the convergence behaviors of the statistical learning algorithm, vanilla Lyapunov learning algorithm, and the proposed online ZFDPP algorithm. Note that the on-grid energy consumption takes negative values for the Lyapunov learning algorithm and the proposed ZFDPP algorithm. This indicates that the developed CoMP system can be purely powered by the green energy while using on-grid energy as a backup power source. The operator of the CoMP system can sell the remaining green energy to the power grid for extra carbon credit. From Fig. 1, we observe that the system running-average weighted throughput and running-average on-grid energy consumption become stable after around $5,000$ iterations. After convergence, the proposed ZFDPP algorithm achieves a better system running-average weighted throughput and running-average on-grid energy consumption than the vanilla Lyapunov learning algorithm based on Fig. 1. This observation verifies that the proposed ZFDPP algorithm converges to a tighter bound in terms of weighted throughput and on-grid energy consumption as shown in Theorem 1. While achieving a lower on-grid energy consumption, the proposed ZFDPP algorithm performs worse that the statistical learning algorithm in terms of running-average weighted throughput. This is due to the fact that the statistical learning algorithm aims at obtain the optimal system weighted throughput. In the next numerical test, we will show that the statistical learning algorithm cannot achieve the flexibility in trading the weighted throughput for the on-grid energy consumption.

Figure 2 shows the tradeoff relation between the system weighted throughput and the on-grid energy consumption. We observe that the vanilla Lyapunov learning algorithm and the proposed ZFDPP algorithm can trade the system throughput for less on-grid energy consumption by increasing the control parameter V. For the statistical learning algorithm, there is no rate-energy tradeoff relation. This is due to the fact that the statistical learning algorithm uses a decaying stepsize to obtain the optimal system throughput while the Lyapunov learning algorithm and the proposed ZFDPP algorithm take the advantage of constant stepsize to achieve the rate-energy tradeoff relation. Besides, we also observe that the proposed ZFDPP algorithm performs better in system weighted throughput and on-grid energy consumption. This is due to the fact that the proposed ZFDPP algorithm can take the advantage of both statistical learning and vanilla Lyapunov learning to achieve a tighter rate-energy bound $[\mathcal{O}(V), \mathcal{O}(\log^2(V)/\sqrt{V})]$ that that of the Lyapunov learning algorithm, i.e., $[\mathcal{O}(V), \mathcal{O}(1/V)]$.

5. CONCLUSIONS

This work investigated the long-term weighted throughput maximization problem for a green CoMP system. Our proposed a zero-forcing dirty paper precoding algorithm takes advantage of both statistical learning and Lyapunov learning. Compared with the Lyapunov learning, the proposed zero-forcing dirty paper precoder achieves a better rate-energy tradeoff relation. Numerical results had been used to demonstrate that the zero-forcing dirty paper precoder outperforms the statistical learning algorithm and the vanilla Lyapunov learning algorithm.

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