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Energy Harvesting Aided Multiuser Transmission in Spectrum Sharing Networks

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ABSTRACT Multiuser transmission with shared spectrum is investigated in the presence of energy harvesting. For each user, the data generation, the harvested energy arrival, and the channel state variation are, respectively, considered as stochastic processes. Each user aims to maximize its own average throughput. Accordingly, a stochastic game is formulated at first. Next, we analyze the stochastic game in infinite-stage and finite-stage scenarios, respectively. On the basis of theoretical studies, an iterated distributive algorithm with solving a linear problem in each iteration is designed for the infinite case. For the finite case, two distributed algorithms named CVPBI and GoPGA are proposed. Finally, the effectiveness of the proposed algorithms is demonstrated by simulations.

INDEX TERMS Energy harvesting, multiuser communication, spectrum sharing, stochastic game.

I. INTRODUCTION

Energy harvesting, which obtains energy from ambient energy sources, has gained much attention because of its ''green'' nature. The energy harvesting aided wireless communication becomes a hot research topic thereby. Generally, these researches can be categorized into two kinds: single user scenario and multiuser scenario. In [1], we have investigated the delay optimal point-to-point transmission, where the data generation, the harvested energy arrival, and the channel state variation are considered. In [2], the cost minimization under delay constraint is performed in multi-carrier single user communications with energy harvesting. In [3], the authors discuss resource allocation strategies of a single user wireless transmission system with hybrid harvesting energy and conventional energy. The authors propose a mixed integer programming problem for minimizing the total energy cost under the energy harvesting constraints as well as an outage constraint. In [4], the energy harvesting single user communication is studied. An asymptotically optimal power allocation solution for optimizing a general utility function is obtained.

With respect to the energy harvesting aided multiuser communication, the interference among users introduces new challenges. In [5], we have studied the energy harvesting aided transmission in cognitive radio networks, where a primary user shares spectrum with an energy harvesting aided secondary user. And two practical algorithms for delay minimization are proposed. In [6], the authors investigate the harvesting symmetric 2-user Gaussian interference channel with energy cooperation. The Han-Kobayashi region of the capacity is characterized. Furthermore, the optimal policy of energy cooperation and power allocation that gets the boundary points on the average rate region is proposed. In [7], a general utility optimization framework for energy-harvesting-based wireless communications is proposed, which encapsulates a series of design problems, e.g., outage probability minimization, in single-user and multiuser setups. In [8], energy reallocation in a multi-user network with a shared harvesting module and storage battery is investigated. In [9], the authors design a joint energy and spectrum cooperation strategy between two renewable powered cellular systems. In [10], multiuser communication with energy harvesting transmitters is analyzed. The intermittence of the harvested energy is taken into account, and the equilibrium's existence and uniqueness of the formulated game are derived. In [11], related works on the energy harvesting wireless communications are summarized and reviewed.

In this paper, we discuss the energy harvesting aided multiuser communication in spectrum sharing networks. Each user is composed of a transmitter and a receiver. The transmitter is equipped with energy harvesting devices such as solar panels. The harvested energy is stored in a battery for possible usage. Meanwhile, the transmitter can get energy from the power grid. Data are generated stochastically in the upper layer of the transmitter and cached in a Fist-in-First-out (FIFO) data buffer. In each transmission, some data are taken from the buffer and transmitted to the receiver. The aim of each user is to maximize the average throughput via scheduling the allocation of the harvested energy and grid power under the grid power constraint.

Compared to previous works, we investigate a more general and practical energy harvesting aided multiuser communications system with sharing spectrum. Besides considering the harvesting energy arrival, the channel variation, and the interplay among users, we take the data generation into account. Furthermore, a unified analytical framework utilizing stochastic game is proposed. Via analytical studies, effective algorithms are designed. The contributions of the paper can be outlined as follows.

- Considering the intermittence of the harvested energy, the channel state variation, the randomness of data arrival at each user and the interaction among users, we formulate a stochastic game [12], [13].
- By exploring the formulated stochastic game in infinite-stage case, an iterated algorithm that derives the Nash equilibrium (NE) is given.
- By analyzing the formulated stochastic game in finite-stage case, two algorithms referred to as CVPBI and GoPGA are respectively proposed for the sufficient data scenario and the general scenario.

The rest of paper is structured as follows. In Section II, the system model is described, and a stochastic game is formulated accordingly. In Section III, the stochastic game is analyzed for infinite and finite time horizon scenarios, and corresponding algorithms are designed thereafter. Next, in Section IV, simulations are performed to verify the effectiveness of proposed algorithms. Finally, Section V concludes the whole paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As illustrated in Fig. 1, consider a spectrum sharing scenario, where M users utilize the same spectrum band in an area. The users are denoted as user $1,\cdots$, user M. Each user consists of a transmitter (Tx) and a receiver (Rx). Each Tx is equipped with energy harvesting devices (e.g., solar panels). The harvested energy is stored in a battery before usage. Meanwhile, each Tx could get power from the grid. At each Tx, generated data from the upper layer are stored in the data buffer as an FIFO queue before transmission. Slotted time model is adopted, and each slot is with length τ. In each slot, the Tx chooses some data from the data queue to transmit to the Rx. We consider block fading model of the wireless channel. That is to say, the channel power gain remains constant in a slot and changes among different slots. $G_{i,j}[n]$ denotes the channel power gain between user i's Tx and user j's Rx in the n-th slot.

Denote the allocated grid power and harvested power of user i for data transmission in the n-th slot as $V_i[n]$ and $W_i[n]$, respectively. The the total power for transmission is

$$\mathcal{P}_i[n] = V_i[n] + W_i[n].$$

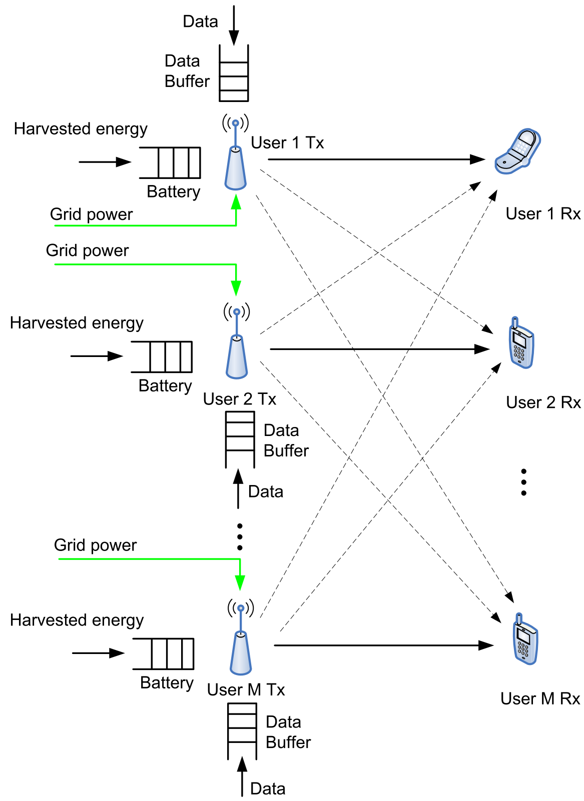

FIGURE 1. **Multiuser transmission in spectrum sharing scenario with energy harvesting.**

The transmitted data during the n-th slot for user i, denoted by $R_i[n]$, can be given by

$$R_i[n] = \log\left(1 + \frac{\mathcal{P}_i[n]G_{i,i}[n]}{\mathcal{I}_i[n]}\right), \tag{1}$$

where

$$\mathcal{I}_i[n] = \sum_{j\neq i, j=1}^{M} \mathcal{P}_j[n]G_{j,i}[n] + N_0$$

denotes the received interference plus noise, and N_0 is the noise power spectral density at the receiver. Denote the stored harvested energy in the user i's battery at the beginning of the n-th slot as $E_i[n]$. $\mathcal{E}_i[n]$ is the harvested energy during the n-th slot at user i. Then

$$E_i[n+1] = E_i[n] - W_i[n]\tau + \mathcal{E}_i[n]. \tag{2}$$

Let $Q_i[n]$ be the data buffer length of user i at the beginning of the n-th slot. Denote $\mathcal{A}_i[n]$ as the generated data from upper layer of user i during the n-th slot. We have

$$Q_i[n+1] = Q_i[n] - R_i[n] + \mathcal{A}_i[n]. \tag{3}$$

Each user decides how much grid power as well as harvested energy to be allocated for data transmission in each slot. And the objective is to maximize its own average throughout under the average grid power consumption constraint during the considered N slots. The set of users is

$$\Omega = \{1, \cdots, M\}.$$

At the n-th slot, denote the state of user i as

$$X_i[n] = \left(Q_i[n], E_i[n], g_{i,j}[n], \mathcal{A}_i[n], \mathcal{E}_i[n]\right)$$

with state space $\mathcal{X}_i$ and the action of user i as

$$S_i[n] = \left(V_i[n], W_i[n]\right)$$

with action space $\mathcal{S}_i$, respectively. Let $\mathcal{S}_i(x)$ be the set of all possible actions of user i in the state $x \in \mathcal{X}_i$. For the state $X_i[n]$, the action should comply with $W_i[n] \leq E_i[n]$ and $R_i[n] \leq Q_i[n]$. If the state of user i at a slot is $x \in \mathcal{X}_i$ and action $s \in \mathcal{S}_i(x)$ is adopted, the next state (state in next slot) will be $z \in \mathcal{X}_i$ with a probability P^i_{xsz}. The payoff to user i is its average throughput, i.e.,

$$u_i = \frac{1}{N}\sum_{n=1}^{N} R_i[n]. \tag{4}$$

Let $\mathcal{X} = \prod_{i\in\Omega} \mathcal{X}_i$, $\mathcal{S} = \prod_{i\in\Omega} \mathcal{S}_i$. The multiuser transmission problem can be formulated as the following constrained stochastic game $\mathcal{G}$.

$$\mathcal{G} = \left\{\Omega, \mathcal{X}, \mathcal{S}, \{P^i_{xsz}\}_{i\in\Omega}, \{u_i\}_{i\in\Omega}\right\} \tag{5}$$

with the average grid power constraint ($\mathcal{V}$ is the upper bound for each user)

$$\bar{V}_i = \frac{1}{N}\sum_{n=1}^{N} V_i[n] \leq \mathcal{V}, \quad \forall i \in \Omega.$$

III. PROBLEM ANALYSIS AND ALGORITHM DESIGN

In this section, the formulated stochastic game is studied and corresponding algorithms are designed for the infinite and finite time slots, respectively. For infinite time slots, the formulated game can be solve through a linear programming (LP) problem, and an iterated algorithm to derive the NE solution is proposed thereafter. For the finite time slots, the optimization problem of each user in the formulated game can be analyzed by using the KKT conditions [17]. Furthermore, the sufficient data case and the general case are investigated, and two algorithms are proposed, respectively.

We first give the definition of the NE for the stochastic game. Define a policy of user i as $\pi_i = \left(\pi_i^1, \cdots, \pi_i^N\right)$ where π_i^n generates an action $s_i = \left(v_i, w_i\right)$ with a probability at the n-th slot. The set of all possible policies of user i is denoted as Π_i. For all the M users, $\Pi = \prod_{i=1}^{M} \Pi_i$ is the set of the multi-policy. The multi-policy excluding user i is expressed as $\pi_{-i} = \left(\pi_1, \cdots, \pi_{i-1}, \pi_{i+1}, \cdots, \pi_M\right) \in \Pi_{-i}$.

Definition 1: The multi-policy $\pi^* = \left(\pi_1^*, \cdots, \pi_M^*\right)$ is a NE if $u_i(\pi^*) \geq u_i(\pi_i, \pi^*_{-i})$ for all $\pi_i \in \Pi_i$ and $i \in \Omega$.

A. INFINITE TIME HORIZON AND FINITE STATE

When $N \to \infty$ and the state is finite, user i solves the following LP problem to obtain its optimal policy (best response) given a multi-policy of other users, π_{-i}. Denote $\mathcal{K}_i = \{(x,s) : x \in \mathcal{X}_i, s \in \mathcal{S}_i(x)\}$, the LP problem is to find $z_i^* = \{z_i^*(x,s) : (x,s) \in \mathcal{K}_i\}$ for

$$\max \sum_{(x,s)\in\mathcal{K}_i} u_{i,\pi_{-i}}(x,s) z_i^*(x,s) \tag{6}$$

$$\text{s.t.} \begin{cases} \sum_{(x,s=(v,w))\in\mathcal{K}_i} v * z_i^*(x,s) \leq \mathcal{V}, & \text{(7a)}\\ \sum_{(x,s)\in\mathcal{K}_i} z_i^*(x,s)\left[\delta_r(x) - P^i_{xsr}\right] = 0, & \\ \qquad \forall r \in \mathcal{X}_i, & \text{(7b)}\\ z_i^*(x,s) \geq 0, \quad \forall (x,s) \in \mathcal{K}_i, & \text{(7c)}\\ \sum_{(x,s)\in\mathcal{K}_i} z_i^*(x,s) = 1. & \text{(7d)} \end{cases}$$

where $u_{i,\pi_{-i}}(x,s)$ is the utility when user i executes s in state x and other users utilize multi-policy π_{-i},

$$\delta_r(x) = \begin{cases} 1, & x = r,\\ 0, & x \neq r. \end{cases}$$

After obtaining z_i^*, the policy that chooses action s for state x with probability

$$P_i^*(s,x) = \frac{z_i^*(x,s)}{\sum_{s'\in\mathcal{S}_i(x)} z_i^*(x,s')} \tag{8}$$

is optimal for user i.

Algorithm 1 Iterated Distributive Algorithm for Obtaining NE Solution

Step 1: $k = 0$, initialize feasible policy for all M users $\{\pi_i(0)\}_{i\in\Omega}$.

Step 2: Update $\pi_i(k+1)$ as the optimal policy (best response) of user i by solving the LP problem (6) given other users' policies, $\pi_{-i}(k)$, for every $i \in \Omega$.

Step 3: $k = k + 1$, go to Step 2 until convergence.

Then, we have an iterated algorithm (Algorithm 1) to get the NE. The optimality of Algorithm 1 in the NE sense can be stated in the following lemma.

Lemma 1: Algorithm 1 derives the NE of the stochastic game for infinite time horizon and finitex state.

Proof: For given $\pi_{-i} \in \Pi_{-i}$, the optimal policy for user i, π_i^*, is given by

$$\pi_i^* = \arg\max_{\pi_i\in\Pi_i} u_i(\pi_i, \pi_{-i})$$
$$\text{s.t. } \bar{V}_i \leq \mathcal{V}. \tag{9}$$

According to the definition of NE i.e., Definition 1, the NE solution of the stochastic game can be verified when π_i^* denotes the optimal policy in (9) for all user i providing other users apply the policies π^*_{-i}. The problem (9) is for a user i given other users' policies. Then the stochastic game shrinks to be a constrained stochastic optimization problem. For the stochastic optimization problem (9), when the time is infinite and the state is finite, it can be transformed to the LP problem (6) [14], [15]. When deriving the optimal solution z_i^*, the probability of choosing action s for state x is $P_i^*(x,s)$. That is to say, the policy that each user $i \in \Omega$ chooses action s for state x with probability $P_i^*(x,s)$ is optimal.

When we get the optimal policy for a user i given other users' policy. The NE solution of all the users's game can be derived by the "best response" iteration algorithm, i.e., Algorithm 1. On the details of the "best response" iteration algorithm, please refer to our previous work [16]. ■

Remark: In Algorithm 1, user i only needs its own information (e.g., the state-action set $\mathcal{K}_i$, the state transition probability P^i_{xsr}), the upper bound of the grid power $\mathcal{V}$, and measures the aggregated received interference from other users $\mathcal{I}_i$. Thus, Algorithm 1 can be distributively applied.

B. FINITE TIME HORIZON

When the time slot is finite, the optimization problem for user i can be expressed as

$$\max_{\{V_i[n], W_i[n]\}_{n=1}^N} \frac{1}{N}\sum_{n=1}^{N} R_i[n] \tag{10}$$

$$\text{s.t.} \begin{cases} W_i[n] \le \frac{E_i[n]}{\tau}, \quad \forall n & (11a)\\ R_i[n] \le Q_i[n], \quad \forall n & (11b)\\ \frac{1}{N}\sum_{n=1}^{N} V_i[n] \le \mathcal{V}. & (11c)\end{cases}$$

where (11a) is the harvested energy causality constraint, (11b) is the instant rate constraint, and (11c) denotes the average grid power constraint. The states $Q_i[n]$ and $E_i[n]$ are related to actions $\big(V_i[n], W_i[n]\big)$ according to (2) and (3), respectively. To avoid the coupling, the constraints are re-expressed as

$$\text{s.t.} \begin{cases} \sum_{n=1}^{l} W_i[n] \le \sum_{n=0}^{l-1} \frac{\mathcal{E}_i[n]}{\tau}, \quad \forall l & (12a)\\ \sum_{n=1}^{l} R_i[n] \le \sum_{n=0}^{l-1} \mathcal{A}_i[n], \quad \forall l & (12b)\\ \frac{1}{N}\sum_{n=1}^{N} V_i[n] \le \mathcal{V}, \quad \forall n. & (12c)\end{cases}$$

where $\mathcal{E}_i[0]$ and $\mathcal{A}_i[0]$ are the initial battery energy and buffer data of user i, respectively.

Using the KKT conditions, the optimal $\big(V_i[k], W_i[k]\big)$ should satisfy

$$\begin{cases} \Big(1-\sum_{j=k}^{N}\psi_j\Big)\frac{G_{ii}[n]}{\mathcal{I}_i[k]+\big(V_i[k]+W_i[k]\big)G_{ii}[n]}\begin{pmatrix}1\\1\end{pmatrix} \\ \quad -\begin{pmatrix}0\\ \sum_{j=k}^{N}\lambda_j\end{pmatrix} - \begin{pmatrix}\rho\\0\end{pmatrix} = 0, \quad \forall k & (13a)\\ \lambda_l\Big(\sum_{n=1}^{l} W_i[n] - \sum_{n=0}^{l-1}\frac{\mathcal{E}_i[n]}{\tau}\Big) = 0, \quad \forall l & (13b)\\ \psi_l\Big(\sum_{n=1}^{l} R_i[n] - \sum_{n=0}^{l-1}\mathcal{A}_i[n]\Big) = 0, \quad \forall l & (13c)\\ \rho\Big(\frac{1}{N}\sum_{n=1}^{N} V_i[n] - \mathcal{V}\Big) = 0 & (13d)\\ \lambda_l \ge 0, \quad \forall l & (13e)\\ \psi_l \ge 0, \quad \forall l & (13f)\\ \rho \ge 0 & (13g)\end{cases}$$

where λ_l, ψ_l, and ρ are generalized Lagrange multipliers.

To derive the optimal solution of the general problem (10) directly from the above equations is challenging if not impossible.

In the following, we first discuss a tractable special scenario where the data are sufficient in each slot. The special case has practical meanings and can be viewed as a relaxed version of (10). After that, we propose a feasible solution of the general scenario.

1) SPECIAL SCENARIO - DATA ARE ENOUGH IN EACH SLOT

When the stored data in the data buffer are enough for each slot transmission, i.e., the upper layer generates data with high velocity, the instant rate constraint is inactive always. Thereafter, we have the following optimization problem for user i.

$$\max_{\{V_i[n], W_i[n]\}_{n=1}^N} \frac{1}{N}\sum_{n=1}^{N} R_i[n] \tag{14}$$

$$\text{s.t.} \begin{cases} \sum_{n=1}^{l} W_i[n] \le \sum_{n=0}^{l-1} \frac{\mathcal{E}_i[n]}{\tau}, \quad \forall l & (15a)\\ \frac{1}{N}\sum_{n=1}^{N} V_i[n] \le \mathcal{V}. & (15b)\end{cases}$$

In (14), the grid power allocation $V_i[n]$ and the harvested energy allocation $W_i[n]$ are optimized simultaneously under the average grid power and harvested energy causality constraints, respectively. According to the principle of "cyclic variable method" in the optimization theory, (14) can be decomposed into two subproblems.

Subproblem 1 (Grid Power Allocation With Average Constraint): In subproblem 1 (i.e., (16)), the optimizing variable is $V_i[n]$ only, and the constraint is the corresponding average grid power constraint.

$$\max_{\{V_i[n]\}_{n=1}^N} \frac{1}{N}\sum_{n=1}^{N} R_i[n]$$
$$\text{s.t.} \ \frac{1}{N}\sum_{n=1}^{N} V_i[n] \le \mathcal{V}. \tag{16}$$

The solution of (16) is

$$V_i^*[n](W_i[n]) = \Big(\frac{1}{\mu_i} - \frac{\mathcal{I}_i[n]}{G_{ii}[n]} - W_i[n]\Big)^+ \tag{17}$$

where

$$(\cdot)^+ = \max\{\cdot, 0\},$$

μ_i is a constant satisfying

$$\sum_{n=1}^{N} V_i^*[n] \le \mathcal{V}.$$

Remark: The solution $V_i^*[n]$ is related to other users' power allocation in the n-th slot (through $\mathcal{I}_i[n]$) as well as $W_i[n]$.

Subproblem 2: Harvested energy allocation with causality constraint

In subproblem 2, i.e., (18), the optimization variable is $W_i[n]$ and the constraint is only the corresponding harvested energy causality constraint.

$$\max_{\{W_i[n]\}_{n=1}^N} \frac{1}{N}\sum_{n=1}^{N} R_i[n]$$
$$\text{s.t.} \sum_{n=1}^{l} W_i[n] \le \sum_{n=0}^{l-1} \frac{\mathcal{E}_i[n]}{\tau}, \quad \forall l. \tag{18}$$

Let $\alpha_n = \frac{G_{i,i}[n]}{\mathcal{I}_i[n]+V_i[n]G_{i,i}[n]}$, $\beta_n = \frac{1}{N}$, $\gamma_n = \frac{1}{\alpha_n\beta_n}$. The solution $\{W_i^*[n]\}_{n=1}^N$ can be given by Algorithm 2 (where the lower index i is omitted for brevity) [5].

Algorithm 2 *HarAlloc*$(N, \{V[n]\}_{n=1}^N)$

Input: N, $\{\mathcal{E}[n]\}_{n=1}^N$, $\{\alpha_n\}_{n=1}^N$
Step 1: $HarAlloc(1) = W^*[1] = \mathcal{E}[0]$.
Step 2:
for $k = 2 : N$
$\{W'[i]\}_{i=1}^{k-1} = HarAlloc(k-1)$
for $r = k : -1 : 1$
$W = \sum_{i=r}^{k-1} W'[i] + \frac{\mathcal{E}[k-1]}{\tau}$
Step 2-1: $\Delta = 0$, $W_M = W^* = W$, $q = r$;
Step 2-2: $\Delta = \Delta + \beta_q$, $W^* = W^* - (\gamma_{q+1} - \gamma_q)\Delta$, $q = q + 1$;
Step 2-3: if $W^* > 0$ and $q \le k$, $W_M = W^*$, repeat Step 2-2;
else $q^* = q - 1$, $W[q^*] = \frac{\beta_{q^*}}{\Delta} W_M$.
end if

$$W^*[q] = \begin{cases} \left[\frac{W[q^*]}{\beta_{q^*}} + \gamma_{q^*} - \gamma_q\right]\beta_q, & r \le q \le q^* \\ 0, & q^* < q \le k. \end{cases}$$

if $r > 1$, $q_e = \max\left\{q \middle| W'[q] > 0, 1 \le q \le r-1\right\}$
else $q_e = 1$.
end if
if $\frac{1}{\alpha_{q^*}\beta_{q^*}} + \frac{W^*[q^*]}{\beta_{q^*}} \ge \frac{1}{\alpha_{q_e}\beta_{q_e}} + \frac{W'[q_e]}{\beta_{q_e}}$
$Alloc(k) = \left\{W'[1], \cdots, W'[r-1], W^*[r], \cdots, W^*[k]\right\}$, break.
end if
end for
end for
Output: $\{W^*[n]\}_{n=1}^N = HarAlloc(N, \{V[n]\}_{n=1}^N)$

Remark: The solution $W_i^*[n]$ is related to other users' power allocation as well as $V_i[n]$.

Based on the analysis and solutions of the two subproblems (Subproblem 1 and Subproblem 2), we give an algorithm (Algorithm 3) for problem (14) in the light of the basic thinking of cyclic variable method.

Remark: Algorithm 3 produces a feasible solution of (14) and gives a lower bound.

Algorithm 3 Iterated Algorithm for a User

Let $\mathbf{V}(k) = \{V^k[n])\}_{n=1}^N$ and $\mathbf{W}(k) = \{W^k[n])\}_{n=1}^N$ be the grid power allocation vector and harvested energy allocation vector, respectively, in the k-th iteration.
Step 1: $k = 0$, initialize feasible policy for user i, $(\mathbf{V}(0), \mathbf{W}(0))$.
Step 2: Update

$$\begin{cases} \mathbf{V}(k+1) = V^*(\mathbf{W}(k)) \\ \mathbf{W}(k+1) = HarAlloc(N, \mathbf{V}(k)) \end{cases}$$

Step 3: $k = k + 1$, go to Step 2 until convergence.

In the above, we investigate the power allocation for a user given other users' power allocations. Based on the algorithm for a user given other users' strategies (Algorithm 3), we propose the Cyclic Variable Principle Based Iteration (CVPBI) algorithm in Table 1 for the M-user under the enough data scenario.

TABLE 1.

CVPBI algorithm
Step 1: $k = 0$, initialize feasible power for all M users, $\mathbf{S}_i(0) = (\mathbf{V}_i(0), \mathbf{W}_i(0))$, $i = 1, \cdots, M$
Step 2: Update $\mathbf{S}_i(k+1)$ using Algorithm 3 given $\mathbf{S}_{-i}(k)$ for each i.
Step 3: $k = k + 1$, go to Step 2 until convergence.

Remark: The CVPBI algorithm gives a feasible solution for the sufficient data scenario. In addition, the CVPBI algorithm requires all-slot (past, current and future) system information (e.g., the energy arrival sequence, data arrival sequence, and channel state sequence) as a priori, and it is an off-line algorithm thereafter. In CVPBI, user i only needs its own system state (e.g., the channel state $G_{i,i}[n]$, harvested energy arrival state $\mathcal{E}_i[n]$), the grid power upper bound $\mathcal{V}$, and measures the received aggregated interference from other users $\mathcal{I}_i[n]$. Then the CVPBI algorithm can be implemented under distributive mode.

2) GREEDY ONE-STAGE GAME POWER ALLOCATION FOR GENERAL SCENARIO

In this section, we propose an on-line algorithm, referred to as Greedy one-stage Game Power Allocation (GoGPA), for the general case. The GoGPA algorithm is a feasible solution of the general problem and gives a lower bound thereafter.

In slot n, the M users run a one-stage game: the player set contains the M users, the strategy of user i is $\mathcal{P}_i[n]$ with constraint

$$\mathcal{P}_i[n] \le \frac{E_i[n]}{\tau} + \Delta_i[n],$$

where $\Delta_i[n]$ is the available grid power at the beginning of the n-th slot. And

$$\Delta_i[n+1] = \Delta_i[n] - V_i[n] \tag{19}$$

with $\Delta_i[1] = N * \mathcal{V}$. The utility of user i is its instant rate

$$R_i[n] = \min\left\{\log\left(1 + \frac{\mathcal{P}_i[n]G_{i,i}[n]}{\mathcal{I}_i[n]}\right), Q_i[n]\right\}.$$

The best response of user i is

$$B\big(\mathcal{P}_{-i}[n]\big) = \min\left\{\frac{E_i[n]}{\tau} + \Delta_i[n], \frac{(e^{Q_i[n]}-1)\mathcal{I}_i[n]}{G_{i,i}[n]}\right\} \quad (20)$$

Algorithm 4 Iterated Algorithm for Obtaining the One-Stage NE

Step 1: $k = 0$, initialize feasible power for all M users, $\mathcal{P}_i^k, i = 1, \cdots, M$

Step 2: Update $\mathcal{P}_i^{k+1} = B\big(\mathcal{P}_{-i}^k\big)$ given $\mathcal{P}_{-i}^k$ for each i.

Step 3: $k = k + 1$, go to Step 2 until convergence.

given other users' power allocations. The NE of this game $\mathcal{P}_i^*[n]$ can be given by Algorithm 4. When obtaining the total transmission power, the grid power and harvested energy allocations are given as follows: If $\mathcal{P}_i^*[n] < E_i[n]$, $W_i[n] = \mathcal{P}_i^*[n]$ and $V_i[n] = 0$. Otherwise, $W_i[n] = E_i[n]$ and $V_i[n] = \mathcal{P}_i^*[n] - E_i[n]$. The GoGPA algorithm is outlined in Table 2.

TABLE 2.

GoGPA algorithm
Step 1: $n = 1$, $\Delta_i[1] = N * \mathcal{V}$, $E_i[1] = \mathcal{E}_i[0]$ and $Q_i[1] = \mathcal{A}_i[0]$ are the initial battery energy and buffer data, respectively.
Step 2: Applying Algorithm 4 to derive the NE solution $\mathcal{P}_i^*[n]$. If $\mathcal{P}_i^*[n] < E_i[n]$, $W_i[n] = \mathcal{P}_i^*[n]$ and $V_i[n] = 0$. Otherwise, $W_i[n] = E_i[n]$ and $V_i[n] = \mathcal{P}_i^*[n] - E_i[n]$.
Step 3: Update $E_i[n+1]$, $Q_i[n+1]$, and $\Delta_i[n+1]$ according to (2), (3) and (21), respectively.
Step 4: $n = n + 1$, go to Step 2 until $n > N$.

Remark: In the n-th iteration of the GoGPA algorithm, only $Q_i[n]$, $E_i[n]$, $\Delta_i[n]$, $G_{i,i}[n]$, and $\mathcal{I}_i[n]$ ($i \in \Omega$) are needed. That is to say, the GoGPA algorithm demands the current-slot system state only, thus it is an on-line algorithm. In the GoGPA algorithm, user i requires only its own state (i.e., $Q_i[n]$, $E_i[n]$, $G_{i,i}[n]$, and $\Delta_i[n]$), the grid power upper bound $\mathcal{V}$, and gauges the received aggregated interference from other users $\mathcal{I}_i[n]$. Hence the GoGPA algorithm is a distributive scheme.

IV. NUMERICAL RESULTS

In this section, simulations are carried out to demonstrate the performance of proposed algorithms. In the simulations, we consider 2 users and 3 slots, i.e., $M = 2$ and $N = 3$. The noise power spectral density $N_0 = 0.1$. The time slot length $\tau = 1$.

A. SUFFICIENT DATA SCENARIO

Fig. 2 demonstrates the convergence performance of the CVPBI algorithm. The fading channel power gains are

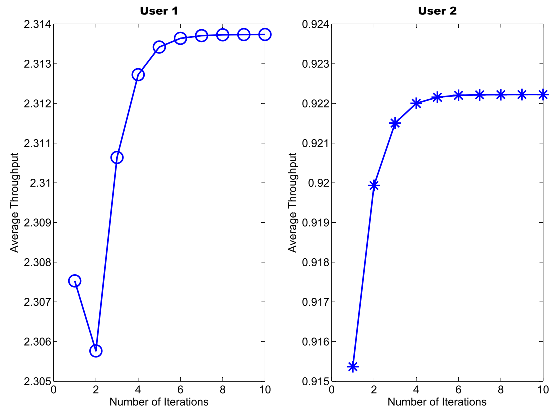

FIGURE 2. Convergence of CVPBI algorithm.

$G_{1,1}$ = [0.3964 0.3952 0.2009], $G_{2,2}$ = [0.0357 0.1061 0.0429], $G_{1,2}$ = [0.0686 0.0714 0.0131], and $G_{2,1}$ = [0.1041 0.0800 0.0037]. The average grid power bound $\mathcal{V} = 250$. The harvested energy arrival $\mathcal{E}_1$ = [50 100 80] and $\mathcal{E}_2$ = [100 50 150]. From the figure, we can observe that the CVPBI algorithm converges with high speed (converges since the 8-th iteration).

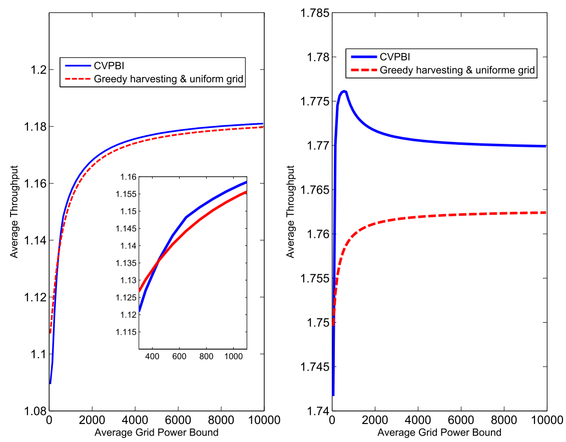

FIGURE 3. The throughput v.s. $\mathcal{V}$.

Fig. 3 plots the average throughput performance of user 1 and user 2 with respect to the average grid power bound $\mathcal{V}$. Meanwhile, we compare the CVPBI with an intuitive scheme referred to as the greedy harvesting & uniform grid scheme, where each user utilizes all the harvested energy in each slot and the grid power is uniformly allocated among slots. Formally, the greedy harvesting & uniform grid scheme can be expressed as

$$\begin{cases} W_i[n] = E_i[n] & (21a) \\ V_i[n] = \dfrac{\mathcal{V}}{N}. & (21b) \end{cases}$$

The fading channel power gains are $G_{1,1}$ = [0.1 0.25 0.2], $G_{2,2}$ = [0.28 0.3 0.5], $G_{1,2}$ = [0.08 0.1 0.05], and $G_{2,1}$ = [0.05 0.08 0.11]. The harvested energy arrival $\mathcal{E}_1$ = [50 100 80] and $\mathcal{E}_2$ = [100 50 150]. From the figure, we can see that the average throughput performance for both users improves first when the average grid power bound increases, and remains constant when $\mathcal{V}$ is larger than some value. The reasons are as follows: When the grid power bound on user 1 and user 2 increases, both user have more power for data transmission, then the throughput increases at first (for user 2, a decrease interval exists since the interference from user 1. When the increasing speed of data transmission power is less than the increasing speed of the interference power, the throughput decreases.). Once the bound is larger than a value, both user 1 and user 2 have enough power for data transmission (When $\mathcal{V}$ is large enough, $V_i[n]$ can be large enough (and must be large enough so as to transmit as much data as possible). Thus, $\mathcal{P}_i[n] = V_i[n] + W_i[n]$ is large enough). Then, for user 1, $R_1[n] = \log\left(1 + \frac{\mathcal{P}_1[n]G_{1,1}[n]}{\mathcal{P}_2[n]G_{2,1}[n]+N_0}\right)$ approaches a constant $\log(1 + \frac{G_{1,1}[n]}{G_{2,1}[n]})$. Similarly, the rate of user 2, $R_2[n] = \log\left(1 + \frac{\mathcal{P}_2[n]G_{2,2}[n]}{\mathcal{P}_1[n]G_{1,2}[n]+N_0}\right)$ approaches $\log(1 + \frac{G_{2,2}[n]}{G_{1,2}[n]})$ with enough transmission power, which is static. Furthermore, from the figure, we can found that the CVPBI has better perfromance than the greedy harvesting & uniform grid scheme. The effectiveness can be verified then.

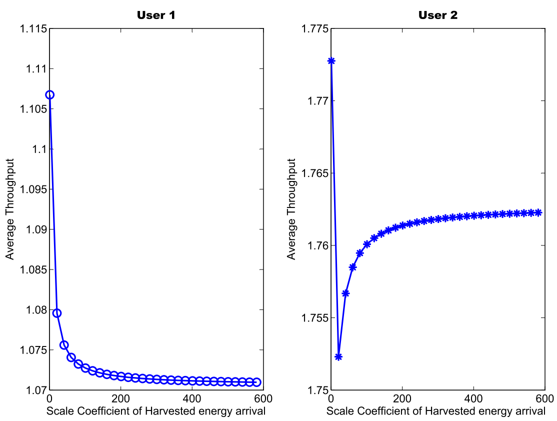

FIGURE 4. The throughput v.s. scale of harvested energy arrival at both user 1 and user 2.

Fig. 4 draws the throughput performance when the harvested energy arrival scales. The harvested energy arrival $\mathcal{E}_1 = [50\ 100\ 80] * \eta$ and $\mathcal{E}_2 = [100\ 50\ 150] * \eta$, where η is referred to as the scaling coefficient. That is to say, the harvested energy scales simultaneously for user 1 and user 2 with coefficient η. The channel power gains are the same as those in Fig. 3. The average grid power bound $\mathcal{V} = 200$. It can be seen that with the increasing of the harvested energy at both users, the average throughput of each user approaches a constant. This is because when the harvested energy is sufficient in each slot, each transmitter allocates power as much as possible. User 1's transmission power is interference for user 2, and vice versa. That is to say, the transmitting power and the interference increase at the same time. For user 1, the increase speed of the interference is higher than that of the transmitting power. Then the rate decrease at first.

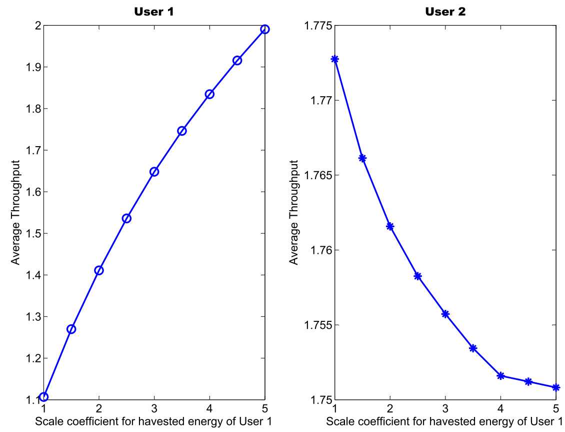

FIGURE 5. The throughput v.s. scale of harvested energy arrival at user 1.

When the arrived harvested energy is large enough, the two increasing speeds become almost the same. Then the throughput remains static. For user 2, the explanations are similar. In contrast, Fig. 5 gives the the throughput performance when the harvested energy arrival scales only at user 1. In this case, the transmitting power of user 1 increases, and the interference for user 2 increases. Thus, the throughput of user 1 increases and that of user 2 decreases.

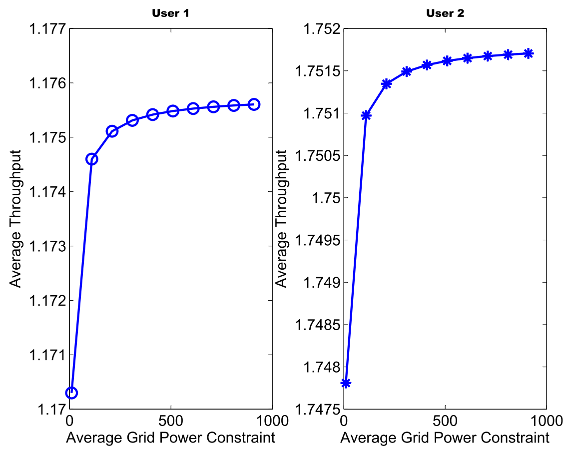

FIGURE 6. The average throughput performance of GoPGA.

B. GENERAL SCENARIO

Fig. 6 illustrates the average throughput performance of the GoPGA algorithm regarding the average grid power bound, $\mathcal{V}$. The channel gains are the same as those in Fig. 3. The harvested energy arrival $\mathcal{E}_1 = \mathcal{E}_2 = [50\ 100\ 80]$. The data arrival $\mathcal{A}_1 = \mathcal{A}_2 = [3\ 8\ 7]$. The initial buffer data is 5. The initial battery energy is 50. From the figure, we can find that the average throughput increases at first with the increase of $\mathcal{V}$, and remains almost constant when $\mathcal{V}$ is larger than some value. It can be explained as follows: With the increase of $\mathcal{V}$, the power budget of users in each one stage game of GoPGA increases. On one hand, the transmission power of both users increases at the NE solution. On the other hand, at one user, the interference from the other user increases at the same time. At first, the transmission power increases faster than that of the interference for both user 1 and user 2, and then the average throughput increases. When $\mathcal{V}$ is large enough, the increase speed of the transmission power is almost the same as that of the interference. Thus the average throughput remains almost constant.

V. CONCLUSION

The energy harvesting aided multiuser communication utilizing shared spectrum is studied in the paper. The average throughput maximization problem is formulated as a stochastic game when generated data, harvested energy, and channel state vary randomly. Two practical algorithms, CVPBI and GoPGA, are designed based on the theoretical analysis of the game. Simulation results verify the effectiveness of the proposed algorithms.

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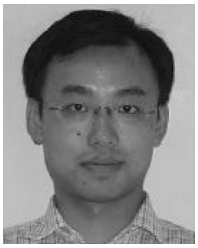

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