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Weighted-Directed-Hypergraph-Based Spectrum Access for Energy Harvesting Cognitive Radio Sensor Network

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ABSTRACT In this paper, we investigate the spectrum access for energy harvesting cognitive radio sensor network (EH-CRSN), where sensor nodes (SNs) connected to different sinks share several channels. To maximize the sum of system energy efficiency (EE) and spectrum efficiency (SE), different from traditional works modeling the interference relationship by binary graph and unweighted hypergraph, we apply a novel weighted directed hypergraph (WDH) to accurately characterize the degree of interference among neighbor SNs and formulate the channel access problem in multi-sink network as a WDH game. We analyze the existence of Nash equilibrium (NE) and design a spectrum access algorithm to achieve the optimal solution which is one of NE. Moreover, simulation results are presented to verify the effectiveness of the proposed algorithm.

INDEX TERMS Weighted directed hypergraph game, spectrum access, energy harvesting, cognitive radio, sensor network.

I. INTRODUCTION

Energy harvesting (EH) and cognitive radio (CR) are expected to provide a new solution to deal with the shortage of energy and spectrum, respectively. However, the efficiency of EH is low and the wireless terminals are growing exponentially, which make the research on increasing energy efficiency (EE) and spectrum efficiency (SE) crucial. Among such research, the appropriate spectrum sharing scheme is a key issue. In this paper, we are concerned with the spectrum access problem for cloud-assisted energy harvesting cognitive radio sensor network (EH-CRSN). In cloud-assisted network, the cloud plays a role as the concentrated controller to control the communication among whole sensor nodes (SNs), while sinks play a role as the cluster head to relay the information of SNs in a local region to the cloud. In this context, since the cloud has more powerful computing and storage capabilities, we can get more exact interference relationship and more complicated optimization objective.

There exist some researches on the spectrum allocation for EH-CRSN. A resource allocation solution was proposed to minimize the energy consumption of battery powered data sensors while spectrum sensors were EH-enabled in [1]. In [2], channel and energy were jointly managed to protect the primary user (PU). In [3], channel access and sampling rate were controlled to maximize the network utility. The previously selected cluster head in [4] assigned channels to SUs based on integer linear program to report their data. In [5], Lyapunov optimization approach was used to jointly control the channel allocation and energy management, in order to maximize the sensed data. The multichannel selection was modeled as a convex optimization problem in [6], which maximized average throughput by controlling the channel selection probability. In [7], considering a realistic rectenna characteristic function, channels for energy harvesting and data transmission were selected simultaneously to improve

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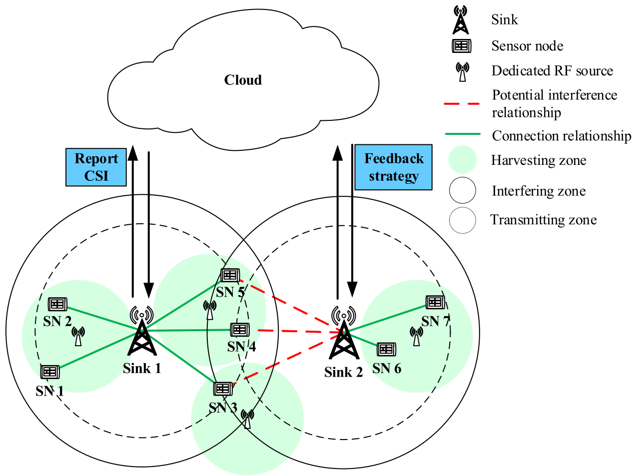


FIGURE 1. Illustration of cloud-assisted EH-CRSN.

system throughput. Multiple users were allowed to transmit on the same channel at the same time in [8] which judged the success of a transmission by the number of users access the same channel. However, the above works only considered the channel allocation within one cluster (sink).

Actually, due to the nature of overlaps of the communication coverage of multiple sinks, SNs connected to different sinks could share the same channel when their interferences are less than the threshold, which provides a possibility of spatial spectrum reuse [9]. Our previous work [10] abstracted the interference relationship of SNs' communications as a binary graph and modeled the channel selection as a binary graph game. However, considering the cumulative effect of weak interference, existing binary graph failing to explore more accumulative interference relationships. As the example in Fig. 1, neither SN 3 nor 5 can collide with the transmission of SN 7 to sink 2, for they are far from sink 2. Whereas, SN 3 and SN 5 can collide with the communication of SN 7 when they transmit simultaneously, for their accumulative interference exceeds the threshold.

To respond to the limitation of binary interference, some hypergraph models have been proposed in the literatures. In [11], [12], [13], hypergraph were introduced to capture the accumulative interference relationship to device-to-device (D2D) networks, small cell networks, and general ad hoc network, respectively. Based on [11], [14] firstly incorporated the directed hypergraph to further represent cumulative and asymmetric interference. The anti-jamming channel selection was further studied in [15], jointly considering the mutual interference and external jamming. However, the aforementioned works can only qualitatively represent the existence of interference rather than quantitatively capture the degree of interference.

In this paper, we propose the weighted directed hypergraph (WDH) based channel allocation for cloud-assisted EH-CRSN. In particular, we firstly analyze the energy and data stored in the SNs, and then give the formula for EE and SE in case of sufficient energy and insufficient energy, respectively. Second, we incorporate the weight vector to propose a general WDH model in cluster network and a WDH game for channel selection. Then, we validate that Nash equilibriums (NEs) exist in the proposed game and one of them is the global optimal solution with the maximal EE and SE. Finally, we design a WDH-based spectrum access algorithm to converge to the optimal NE solution. To the best of our knowledge, this is the first work to incorporate the WDH into the wireless resource management.

The rest of the paper is organized as follows. The system model is given in Section II. The problem formulation is presented in Section III. In Section IV, we propose a centralized-distributed spectrum access algorithm. The simulation results are conducted in Section V, and the conclusion is given in Section VI.

II. SYSTEM MODEL

As shown in Fig. 1, we consider a cloud-assisted EH-CRSN consisting of one cloud, a set of N sink nodes (access point) $\mathcal{N} = \{1, 2, \ldots, N\}$, a set of M SNs $\mathcal{M} = \{1, 2, \ldots, M\}$, and a set of D dedicated radio frequency (RF) sources $\mathcal{D} = \{1, 2, \ldots, D\}$. Dedicated RF sources are powered via wire. Besides, the position of RF sources is fixed. Each SN establishes connection with the nearest sink as long as the distance between SN and sink d_T is less than the maximum transmission distance r_T. Besides, each SN senses the information in a certain distance range and sends the generated data to network through the connected sink. Meanwhile, sinks would be interfered by the SNs those are located within the interference distance r_I ($r_I > r_T$). Define the interfering zone and transmitting zone as the disk with radius r_I and r_T centered at a sink, respectively. It is assumed that the interference generated by SNs outside the interference zone is ignored. And denote $\mathcal{C}_s$ and $\mathcal{I}_s$ as the set of connecting SNs and the set of interfering SNs of sink s, respectively. What's more, SNs opportunistically access Q orthogonal channels $\mathcal{Q} = \{1, 2, \ldots, Q\}$ under the control of cloud. Specifically, each SN i is allowed to select one (possibly empty) from available channel set $\mathcal{A}_i \subseteq \mathcal{Q}$. And SNs connect the same sink should select different channels.

In terms of energy, SNs harvest RF energy for energy supply and we define the harvesting zone as the disk with radius r_H centered at RF source. It is supposed that each SN locates in the harvesting zone of at least one RF source. We denote $\mathcal{R}_i$ as the set of RF sources whose harvesting zone can cover SN i.

A. TIME SLOT STRUCTURE

In the beginning, it takes a period of time to complete the network parameters initialization in cloud. In this phase, each SN $i \in \mathcal{M}$ reports energy harvesting efficiency η_i, average energy expended in data generating β_i (measured in Joule/bit), and data generating rate v_i (measured in bits/s). η_i and β_i are determined by the hardware of sensors, and v_i is preset based on user preference. At the same time, each sink $s \in \mathcal{N}$ detects the received power $P_s^i = P_{Ti} {d_{i,s}}^{-\alpha}$ of the signal

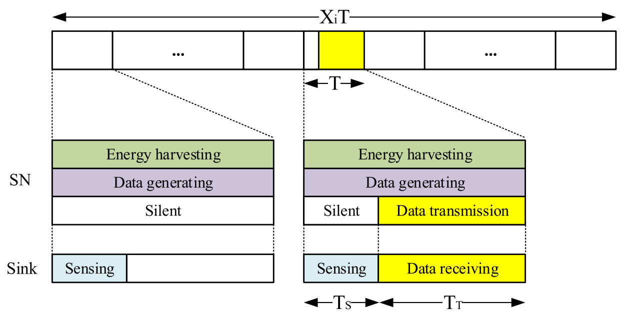


FIGURE 2. Illustration of time slot structure.

sent by each SN i in their interfering zone, where P_{Ti} is the transmit power of SN, $d_{i,s}$ is the distance between i and s, and α is path loss exponent. Note that sink directly detects P_s^i, and the formula of P_s^i is written for facilitating the analysis. Then, sinks report these initialization parameters to cloud and the cloud stores them for subsequent channel selection.

Specifically, PUs and the CR network both work in a synchronous slotted model [16]. We denote $\mathcal{M}_A(t) \subseteq \mathcal{M}$ as the set of active SNs which have enough energy and data for one transmission. At the beginning of slot t, new active SNs would request for transmission while the others would keep silent. At the same time, each new active SN $i \in \mathcal{M}_A(t)$ reports individual energy harvesting rate h_i to the connected sink which equals to $\sum_{j\in\mathcal{R}(i)} P_H {d_{i,j}}^{-\alpha}$ where P_H is transmit power of RF source. Then, sinks perform spectrum sensing to get the channel state information (CSI). In addition, it is assumed that the spectrum sensing is perfect. Next, sinks report energy harvesting rates and current CSI to cloud. Afterwards, cloud makes channel access decision according to the initialization parameters, energy harvesting rates and channel state, where the initialization parameters are uploaded when SNs initially join the network. After that, cloud feeds back its decisions on channel access strategy to sinks to broadcast to SNs and delete the SNs transmit in this slot. Finally, SNs transmit data to network through the connected sink according to the channel access strategy. The time slot structure of new active SNs is illustrated in Fig. 2. It is assumed that the slot duration is T and the spectrum sensing duration is T_S. The data transmitting duration is $T_T = T - T_S$, since the time spent reporting the current information and feeding back decision is marginal compared to the time spent on spectrum sensing and data transmission. Besides, we assume that data generating and energy harvesting can take place simultaneously.

B. TRANSMISSION CYCLE

Each SN may harvest a tiny amount of RF energy in one time slot due to severe channel fading and path loss, which are caused by poor channel quality or long transmission distance. So SNs may take a long time to harvest enough energy for transmission. Besides, there is not always generated data waiting to be transferred. Thus, because of the limitation of harvested energy and generated data, SNs could only periodically transmit data. For a better analyzing of the EE and SE, let's define the transmission cycle as the shortest transmitting interval of each SN. That is, each SN must harvest energy and generate data for at least one transmission cycle before conducting transmission. We denote X_iT as the transmission cycle of SN i.

TABLE 1. Changes of energy and data in one transmission cycle.

	increase	decrease
energy	$X_iT\eta_ih_i$	$X_iTv_i\beta_i + P_{Ti}T_T$
data	X_iTv_i	$WT_T\log\left(1+\frac{P_{Ti}{d_{i,s_i}}^{-\alpha}}{I_i+N_0}\right)$

Then, the harvested energy and the consumed energy of SN i in one transmission cycle can be computed by $X_iT\eta_ih_i$ and $X_iTv_i\beta_i + P_{Ti}T_T$, respectively. We denote s_i as the connecting sink of SN i. And the generated data and transmitted data can be computed by X_iTv_i and $WT_T\log\left(1+\frac{P_{Ti}{d_{i,s_i}}^{-\alpha}}{I_i+N_0}\right)$, respectively, where W is the bandwidth of each channel, I_i is the jamming power which will be discussed in Section III. C, and N_0 is the noise power. The changes of energy and data of SN i in one transmission cycle are summarized in Table 1.

(1) *Case 1:* RF energy supply is adequate. The energy harvested in one transmission cycle is larger than the consumed energy in this case, which makes the transmission cycle determined by the rate of generating the sensed data. That is, SN is able to transmit the data if and only if it has generated enough data to perform one transmission. Here, one transmission refers to the transmission within one time slot. Then, $X_iTv_i = WT_T\log\left(1+\frac{P_{Ti}{d_{i,s_i}}^{-\alpha}}{I_i+N_0}\right)$ for the generated data in a transmission cycle is equal to the transmitted data. Thus, the transmission cycle is

$$X_iT = \frac{WT_T\log\left(1+\frac{P_{Ti}{d_{i,s_i}}^{-\alpha}}{I_i+N_0}\right)}{v_i} \tag{1}$$

(2) *Case 2:* In the just-right scenario, the time it takes to sense enough data for one transmission is exactly equal to the time it takes to harvest enough energy for one transmission. In this extreme case, the transmission cycle is

$$X_iT = \frac{WT_T\log\left(1+\frac{P_{Ti}{d_{i,s_i}}^{-\alpha}}{I_i+N_0}\right)}{v_i} = \frac{P_{Ti}T_T}{\eta_ih_i - v_i\beta_i} \tag{2}$$

(3) *Case 3:* RF energy supply is insufficient. In this case, it takes a long time to harvest energy, which makes the transmission cycle is determined by the rate of energy harvesting. That is, in a transmission cycle, the harvested energy $X_iT\eta_ih_i$ is equal to the consumed energy of data generating and transmitting $X_iTv_i\beta_i + P_{Ti}T_T$. Thus, the transmission cycle is

$$X_iT = \frac{P_{Ti}T_T}{\eta_ih_i - v_i\beta_i} \tag{3}$$

TABLE 2. **Transmission cycle under three cases.**

Cases	Energy	Data	Transmission cycle
energy surplus	$X_iT\eta_ih_i > X_iTv_i\beta_i + P_{Ti}T_T$	$X_iTv_i = WT_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)$	$X_iT = \frac{WT_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)}{v_i}$
energy balance	$X_iT\eta_ih_i = X_iTv_i\beta_i + P_{Ti}T_T$	$X_iTv_i = WT_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)$	$X_iT = \frac{WT_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)}{v_i} = \frac{P_{Ti}T_T}{\eta_ih_i-v_i\beta_i}$
energy deficit	$X_iT\eta_ih_i = X_iTv_i\beta_i + P_{Ti}T_T$	$X_iTv_i > WT_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)$	$X_iT = \frac{P_{Ti}T_T}{\eta_ih_i-v_i\beta_i}$

The transmission cycle of SN i under different three cases are summarized in Table 2. Note that the transmission cycle is a time-variant value which is determined by location of SNs. In this paper, we assume SNs move slowly so that their positions will not change for at least one transmission cycle.

C. ENERGY EFFICIENCY AND SPECTRUM EFFICIENCY

With the derived transmission cycle, we could analyze the EE and SE of single SN. The EE (measured in bits/Joule/Hz) of SN i is defined as the energy consumed per bit in unit bandwidth [17]. Owing to the assumption that the positions of SNs stay the same in one transmission cycle, the EE of SN i can be formulated as

$$EE_i = \frac{\theta_i T_T}{W\left(X_iTv_i\beta_i + P_{Ti}T_T\right)} = \frac{T_T\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)}{X_iTv_i\beta_i + P_{Ti}T_T} \tag{4}$$

where

$$\theta_i = W\log\left(1+\frac{P_{Ti}d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right) \tag{5}$$

is the channel capacity between SN i and the connected sink. Similarity, the SE (measured in bits/s/Hz) of SN i is defined as the transmission rate per unit bandwidth which can be formulated as

$$SE_i = \frac{\theta_i T_T}{TW} = \frac{T_T\log\left(1+\frac{P_T d_{i,s_i}{}^{-\alpha}}{I_i+N_0}\right)}{T} \tag{6}$$

III. PROBLEM FORMULATION

For the promotion of system EE and system SE of EH-CRSN, we need quantitatively describe the local interaction relationship. In this section, we first present and analyze the existing directed hypergraph model. Then, a novel WDH model applies to clustered network is illustrated. Finally, we proposed the WDH-based spectrum access algorithm.

A. EXISTING DIRECTED HYPERGRAPH

Before introducing the existing directed hypergraph model in channel allocation, we introduce some preliminaries of directed hypergraph [18].

Definition 1 Directed hypergraph: Let $\mathcal{V} = \{v_1, v_2, \ldots, v_V\}$ *be a finite set, a directed hypergraph* H *on* $\mathcal{V}$ *is a family*

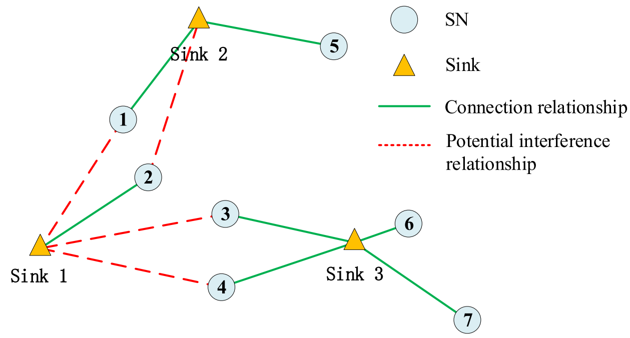


FIGURE 3. **A simple network with 3 sinks and 7 SNs.**

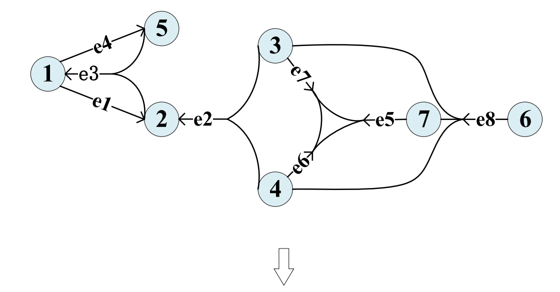
$\mathcal{E} = (e_1, e_2, \ldots, e_E)$ *of subset of* $\mathcal{V}$*, such that*

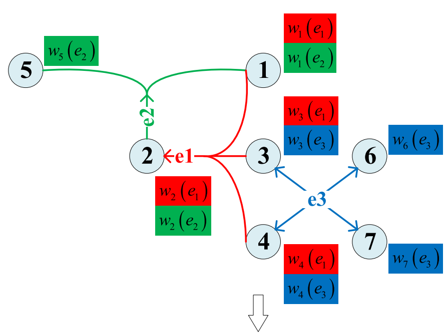
$$\begin{aligned} & e_n \neq \emptyset\,(n = 1, 2, \ldots, V) \\ & \bigcup_{n=1}^{V} e_n = \mathcal{V} \end{aligned} \tag{7}$$

The elements $v_1, v_2, \ldots v_V$ *of* $\mathcal{V}$ *are vertices of directed hypergraph* H*, and the sets* $e_1, e_2, \ldots, e_E$ *are the directed hyperedges of directed hypergraph* H*. A directed hyperedge* $e_n = (\mathcal{T}(e_n), \mathcal{H}(e_n))$ *is an ordered pair of disjoint subsets of vertices, where* $\mathcal{T}(e_n)$ *is the tail set of* e_n *and* $\mathcal{H}(e_n)$ *is the head set.*

1) Directed Hypergraph Construction: The intension of existing directed hypergraph in [14] is to capture the asymmetric cumulative interference effect in D2D networks. For the considered EH-CRSN in Section III, we formulate the directed hypergraph $H = \left(\mathcal{M}, \mathcal{E} = (e_n)_{n\in\Lambda}\right)$ (Λ is a finite set of indexes, $E = |\Lambda|$) by referring the SN set $\mathcal{M}$ as the vertex set and referring the asymmetric cumulative interference relationships as the directed hyperedge set $\mathcal{E} \subseteq \mathcal{M} \times \mathcal{M}$. In one directed hyperedge, refer the interfering SNs as the head set and the interfered SNs as tail set. Besides, if all the head vertices in a hyperedge transmit on the same channel with one tail vertex, the SINR of the tail vertex is less than the worst case transmitting SINR. Furthermore, for one directed hyperedge, if any head vertex is removed, the remaining head vertices would not collide with the tail vertex for the cumulative interference are less than threshold.

2) Incidence Matrix of Directed Hypergraph: The directed hypergraph can be specified from its one to one corresponding incidence matrix [19]. In an incidence matrix, each row corresponds to one vertex and each column corresponds to





Incidence Matrix

SN	e1	e2	e3	e4	e5	e6	e7	e8
1	1	0	-1	1	0	0	0	0
2	-1	-1	1	0	0	0	0	0
3	0	1	0	0	-1	-1	1	-1
4	0	1	0	0	-1	1	-1	-1
5	0	0	1	-1	0	0	0	0
6	0	0	0	0	0	0	0	1
7	0	0	0	0	1	-1	-1	-1

(a)

Incidence Matrix

SN	e1	e2	e3
1	$\omega_1(e_1)$	$\omega_2(e_2)$	0
2	$\omega_2(e_1)$	$\omega_3(e_2)$	0
3	$\omega_3(e_1)$	0	$\omega_3(e_3)$
4	$\omega_4(e_1)$	0	$\omega_4(e_3)$
5	0	$\omega_5(e_2)$	0
6	0	0	$\omega_6(e_3)$
7	0	0	$\omega_7(e_3)$

(b)

FIGURE 4. **Illustration of the directed hypergraph model and the proposed WDH model of the network shown in Fig. 3, and their incidence matrixes. Note that in WDH, we use different colors to distinguish the weights of different hyperedge.**

one hyperedge. If vertex v_m belongs to the head set of hyperedge e_n, then (m, n)-entry in the matrix is 1; if vertex v_m belongs to its tail set, then (m, n)-entry is -1; otherwise, it is 0. As an example, Fig. 4(a) illustrates the directed hypergraph model of a simple network in Fig. 3 and gives the incidence matrix.

As mentioned above, directed hypergraph qualitatively capture the asymmetric cumulative interference relationships. Since head vertices in $\mathcal{H}(e_n)$ is assumed to has the same degree of interference with different tail vertices in $\mathcal{T}(e_n)$, the throughput formula (5) becomes unavailable. Existing works describe the throughput in the binary normalized form. That is, the goal is maximizing the normalized network capacity or minimizing the system MAC-layer interference. However, maximizing the system EE and SE not only depends on the interference relationships, but also on the actual SINR of SN. The root cause is that the interference degrees of vertices in one hyperedge are different. Obviously, we need a more accurate model to describe the interference relationship to improve the spectrum access strategy.

B. PROPOSED WDH MODEL

In order to maximize the system EE and SE of clustered network, we extend the existing directed hypergraph model to a WDH model [18] which takes the exact interference degree into account and is more succinct.

Definition 2 Weighted directed hypergraph: An WDH is a tuple $\langle \mathcal{V}, \mathcal{E}, \mathcal{W} \rangle$, where $\mathcal{V}$ is a finite set of vertices, $\mathcal{E}$ is a finite set of hyperedge, and $\mathcal{W}$ is the set of weights. A hyperedge $e \in \mathcal{E}$ is a triple $e = \langle \mathcal{H}(e), \mathcal{T}(e), \omega(e) \rangle$, where $\mathcal{H}(e) \subseteq \mathcal{V}$ is the head set, $\mathcal{T}(e) \subseteq \mathcal{V}$ is the tail set, and $\omega(e)$ is a hyperedge weight vector.

1) WDH Construction: Unlike existing hypergraph model makes the smallest interfering SNs set and their common interfered SNs set form a hyperedge, which applied to D2D communication networks, the proposed WDH model makes the interfering SNs and the connecting SNs of sink $n \in \mathcal{N}$ together form a hyperedge e_n, which applied to clustered communication networks. Specifically, in hyperedge e_n, refer the interfering SNs set $\mathcal{I}_n$ as the head set $\mathcal{H}(e_n)$ and refer the connecting SNs set $\mathcal{C}_n$ as the tail set $\mathcal{T}(e_n)$. As an example, the EH-CRSN in Fig. 1 consists of two hyperedges. One edge is made up of SNs 1, 2, 3, 4 and 5 which are all tail vertices. And the other edge is made up of SNs 3, 4, 5, 6 and 7, with SNs 3, 4 and 5 as the head vertices and SNs 6 and 7 as tail vertices. The concrete absolute value of vertex weight $|\omega_m(e_n)|$, $m \in \mathcal{I}_n \cup \mathcal{C}_n$ in hyperedge e_n may depend on specific problem, but should obey the general rule that $|\omega_m(e_n)|$ should positively relate with the contribution of interference relationship of sink n. Moreover, the interfering SNs and the connecting SNs of one sink can all be regarded as the interference sources that interfere with the sink's wireless communication. That is, $|\omega_m(e_n)|$ is exactly a measure of the received power P_n^m of the signal sent by SN m to sink n. In this way, the hyperedge weight vector provides the feasibility of distinguishing the interference degree of different SNs. In this paper, the weight vector $\omega_m(e_n)$ is defined as follows:

$$\omega_m(e_n) = \begin{cases} P_{Tm} {d_{m,n}}^{-\alpha}, & m \in \mathcal{H}(e_n) \\ -P_{Tm} {d_{m,n}}^{-\alpha}, & m \in \mathcal{T}(e_n) \end{cases} \tag{8}$$

2) Incidence Matrix of WDH: According to (8), the incidence matrix of WDH can be written as

$$b_{mn} = \begin{cases} \omega_m(e_n), & m \in \mathcal{H}(e_n) \cup \mathcal{T}(e_n) \\ 0, & otherwise \end{cases} \tag{9}$$

which is an $M \times N$ matrix $B = [b_{mn}]_{M \times N}$. As an example, Fig. 4(b) shows a weighted directed hypergraph model and its incidence matrix of the network in Fig. 3. In the next subsection, we discuss the optimization problem based on the proposed WDH model.

C. OPTIMIZATION PROBLEM

Given the WDH model, we first denote the selected channel of SN i as $a_i \in \mathcal{A}_i$ which is 0 when no transmission is attempted. Let $\boldsymbol{a} = (a_1, a_2, \ldots, a_M)$ be the joint strategy profile of all SNs with space $\mathcal{A} = \underset{i \in \mathcal{M}}{\times} \mathcal{A}_i$. Then, we introduce inter-sink interference $\delta_j^i(a_i, \boldsymbol{a}_{-i})$ and intra-sink interference $\varphi_i(a_i, \boldsymbol{a}_{-i})$ which are two binary variables. $\delta_j^i(a_i, \boldsymbol{a}_{-i})$ specifying whether SN $j \in \mathcal{I}_{s_i}$ actually interferes with SN i, as follows:

$$\delta_j^i(a_i, \boldsymbol{a}_{-i}) = \begin{cases} 1, & a_i \neq 0, a_j = a_i, j \in \mathcal{H}\left(e_{s_i}\right) \\ 0, & otherwise. \end{cases} \tag{10}$$

$\varphi_i(a_i, \boldsymbol{a}_{-i})$specifying whether any SN $\forall j \in \mathcal{C}_{s_i}, j \neq i$ collides with SN i, as follows:

$$\varphi_i(a_i, \boldsymbol{a}_{-i}) = \begin{cases} 1, & a_i \neq 0, a_j = a_i, \forall j \in \mathcal{T}\left(e_{s_i}\right), j \neq i \\ 0, & otherwise. \end{cases} \tag{11}$$

where $\boldsymbol{a}_{-i}$ is the strategy vector of all SNs except for SN i. Accordingly, given the channel selection strategy profile $\boldsymbol{a} = (a_i, \boldsymbol{a}_{-i})$, the cumulative interference which equals to the jamming power applied on SN i is defined as

$$\begin{aligned} I_i(\boldsymbol{a}) &= \sum_{j \in \mathcal{I}_{s_i}, j \neq i} \delta_j^i P_{Ti} {d_{j,s_i}}^{-\alpha} \\ &= \sum_{j \in \mathcal{I}_{s_i}, j \neq i} \delta_j^i \omega_j\left(e_{s_i}\right). \end{aligned} \tag{12}$$

Thus, the SINR of SN i is $\gamma_i(\boldsymbol{a}) = \frac{|\omega_i(e_{s_i})|}{I_i(\boldsymbol{a})+N_0}$ and we denote the worst case transmitting SINR as $\gamma_{\min}$. Obviously, when $\gamma_i(\boldsymbol{a}) \geq \gamma_{\min}$, SN i can decode the packet correctly; when $\gamma_i(\boldsymbol{a}) < \gamma_{\min}$, the communication of SN i collides. So, we define an indicator function as follows:

$$\chi_i(\boldsymbol{a}) = \begin{cases} 1, & \dfrac{\left|\omega_i\left(e_{s_i}\right)\right|}{I_i(\boldsymbol{a}) + N_0} \geq \gamma_{\min} \\ 0, & otherwise. \end{cases} \tag{13}$$

Hence, the throughput of SN i is given by

$$\begin{aligned} \theta_i(\boldsymbol{a}) &= \chi_i(\boldsymbol{a})(1 - \varphi_i(\boldsymbol{a}))W \log\left(1 + \frac{P_{Ti} {d_{i,s_i}}^{-\alpha}}{I_i(\boldsymbol{a}) + N_0}\right) \\ &= \chi_i(\boldsymbol{a})(1 - \varphi_i(\boldsymbol{a}))W \log(1 + \gamma_i(\boldsymbol{a})). \end{aligned} \tag{14}$$

According to (14), the EE and the SE of SN i could be respectively expressed as

$$EE_i(\boldsymbol{a}) = \frac{\chi_i(\boldsymbol{a})(1 - \varphi_i(\boldsymbol{a}))W \log(1 + \gamma_i(\boldsymbol{a}))T_T}{W(X_i T v_i \beta_i + P_{Ti} T_T)} \tag{15}$$

$$SE_i(\boldsymbol{a}) = \frac{\chi_i(\boldsymbol{a})(1 - \varphi_i(\boldsymbol{a}))W \log(1 + \gamma_i(\boldsymbol{a}))T_T}{TW}. \tag{16}$$

Define the sum of EE and SE of SN i as:

$$\phi_i(\boldsymbol{a}) = EE_i(\boldsymbol{a}) + SE_i(\boldsymbol{a}) \tag{17}$$

Let $U(\boldsymbol{a})$ denote the sum of system EE and system SE as

$$U(\boldsymbol{a}) = \sum_{i \in \mathcal{M}} \phi_i(\boldsymbol{a}). \tag{18}$$

Finally, we have the optimization problem that

$$\begin{aligned} \max_{\boldsymbol{a}=(a_1,a_2,\ldots a_M)} \; & U(\boldsymbol{a}) = \sum_{i \in \mathcal{M}} \phi_i(\boldsymbol{a}) \\ s.t. \; & a_i \in \mathcal{A}_i, i = 1, 2, \ldots, M \end{aligned} \tag{19}$$

In the next subsection, we construct a WDH game to solve this optimization problem.

D. PROPOSED WDH GAME

Firstly, we give the definition of WDH game as follows:

Definition 3 WDH game: The WDH game is $\mathcal{G} = \left(\mathcal{M}, \{\mathcal{A}_i\}_{i \in \mathcal{M}}, \{\omega(e)\}_{e \in \mathcal{E}}, \{u_i\}_{i \in \mathcal{M}}\right)$ *where the SN set* $\mathcal{M}$ *is the player set, the available channel set* $\mathcal{A}_i$ *is the strategy set of player i,* u_i *is the utility function of player i.*

To achieve the optimization object, the remaining issue is designing the utility function for SNs. For convenience, we denote the SNs may be interfered by SN i as $\mathcal{Z}_i = \left\{j | d_{i,s} < r_I, s \in \mathcal{N}, j \in \mathcal{C}_s, j \neq i\right\}$. As the example in Fig. 3, for SN 3, $\mathcal{Z}_3 = \{2, 4, 6, 7\}$. In this paper, the utility function of SN i is defined as

$$u_i(\boldsymbol{a}) = \phi_i(\boldsymbol{a}) + \sum_{j \in \mathcal{Z}_i} \phi_j(\boldsymbol{a}) \tag{20}$$

which is inspired by [20]. Note that the utility function is able to enforce the network to get the equilibriums with the maximum objective, which will be proved in the following.

Then, we discuss the equilibrium of the WDH game. We present the definition of pure Nash equilibrium (PNE) as follows:

Definition 4 PNE: A joint strategy profile $\boldsymbol{a}^* = \left(a_1^*, a_2^*, \ldots, a_M^*\right)$ *is PNE if and only if no player can increase its utility by unilaterally deviating its strategy. Namely, the PNE satisfies*

$$u_i\left(\boldsymbol{a}^*\right) \geq u_i\left(a_i, \boldsymbol{a}_{-i}^*\right), \forall i \in \mathcal{M}, \forall a_i \in \mathcal{A}_i. \tag{21}$$

In the following, we formally validate that PNE does exist.

Theorem 1: The WDH game with weight vector in (8) possesses at least one PNE. The point with maximal sum of system EE and system SE in (18) constitutes one PNE.

Proof: Firstly, we denote the SNs that may interfere with SN i as $\mathcal{J}_i = \left\{j | j \in \mathcal{C}_{s_i} \cup \mathcal{I}_{s_i}, j \neq i\right\}$. As the example in Fig. 3, for SN 3, $\mathcal{J}_3 = \{4, 6, 7\}$. Since the sum of EE and SE of SN

i is only influenced by SNs in $\mathcal{J}_i$, the sum of its EE and its SE could be written as $\phi_i(a_i, \boldsymbol{a}_{-i}) = \phi_i(a_i, \boldsymbol{a}_{\mathcal{J}_i})$ where $\boldsymbol{a}_{\mathcal{J}_i}$ is the strategy profile of SNs in $\mathcal{J}_i$.

Suppose any SN i improves the sum of its EE and its SE by unilaterally change its strategy from a_i to a_i', then the change in the utility of SN i is

$$\begin{aligned} &u_i(a_i', \boldsymbol{a}_{-i}) - u_i(a_i, \boldsymbol{a}_{-i}) \\ &\quad = \left[\phi_i(a_i', \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j(a_i', \boldsymbol{a}_{\mathcal{J}_i})\right] \\ &\quad - \left[\phi_i(a_i, \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j(a_i, \boldsymbol{a}_{\mathcal{J}_i})\right] \end{aligned} \tag{22}$$

Besides, from (18), we derive the change in the sum of system EE and system SE from SN' s strategy in (23).

$$\begin{aligned} U(a_i', \boldsymbol{a}_{-i}) - U(a_i, \boldsymbol{a}_{-i}) &= \sum_{j\in\mathcal{M}} \phi_j(a_i', \boldsymbol{a}_{-i}) - \sum_{j\in\mathcal{M}} \phi_j(a_i, \boldsymbol{a}_{-i}) \\ &= \left[\phi_i(a_i', \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j\left(a_j, \boldsymbol{a}'_{\mathcal{J}_j}\right) + \sum_{\substack{j\in\mathcal{M}, j\notin\mathcal{Z}_i,\\ j\neq i}} \phi_j\left(a_j, \boldsymbol{a}'_{\mathcal{J}_j}\right)\right] \\ &= \left[\phi_i(a_i, \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j\left(a_j, \boldsymbol{a}_{\mathcal{J}_j}\right) + \sum_{\substack{j\in\mathcal{M}, j\notin\mathcal{Z}_i,\\ j\neq i}} \phi_j\left(a_j, \boldsymbol{a}_{\mathcal{J}_j}\right)\right] \end{aligned} \tag{23}$$

For any SN $j \in \mathcal{M}, j \notin \mathcal{Z}_i, j \neq i$, set $\mathcal{J}_j$ doesn't include SN i. Thus, we have

$$\sum_{j\in\mathcal{M}, j\notin\mathcal{Z}_i, j\neq i} \phi_j\left(a_j, \boldsymbol{a}'_{\mathcal{J}_j}\right) = \sum_{j\in\mathcal{M}, j\notin\mathcal{Z}_i, j\neq i} \phi_j\left(a_j, \boldsymbol{a}_{\mathcal{J}_j}\right) \tag{24}$$

From (24), (23) can be expressed by

$$\begin{aligned} &U(a_i', a_{-i}) - U(a_i, a_{-i}) \\ &\quad = \left[\phi_i(a_i', \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j(a_i', \boldsymbol{a}_{\mathcal{J}_i})\right] \\ &\quad - \left[\phi_i(a_i, \boldsymbol{a}_{\mathcal{J}_i}) + \sum_{j\in\mathcal{Z}_i} \phi_j(a_i, \boldsymbol{a}_{\mathcal{J}_i})\right] \end{aligned} \tag{25}$$

Obviously, the change in SN' s utility equals to the change in the sum of system EE and system SE. According to the definition of exact potential game (EPG) [21], the WDH game is an EPG and the sum of system EE and system SE constitutes the potential function. Since EPG has at least one PNE that maximizes the potential function [20], the WDH game possesses one PNE with maximal sum of system EE and system SE. Therefore, Theorem 1 is proved. ■

IV. WDH-BASED SPECTRUM ACCESS ALGORITHM

The framework we proposed above is generic in which many learning algorithms can be applied. spatial adaptive play (SAP) is a learning algorithm which has been proved in [20] that it can converges to PNE in potential game and guarantee to maximize the potential function with an arbitrarily high probability. The kernel of the SAP is: randomly select exactly one SN to update its channel selection according to its strategy probability distribution while other SNs repeat their selection. Based on SAP, we desire a practical for energy-efficient and spectrum-efficient dynamic spectrum access in EH-CRSN.

Algorithm 1 WDH-Based Spectrum Access Algorithm

(1) Hypergraph Construction

1: Each SN i establishes a connection to the nearest accessible sink to report energy harvesting efficiency η_i, average energy expended in data generating β_i, data generating rate v_i, and individual energy harvesting rate h_i to the sink. Each sink s detects the received power P_s^i of the signal sent by each SN i in their interfering zone. Then, each sink s reports the connecting SNs set $\mathcal{C}_s$, the interfering SNs set $\mathcal{I}_s$ and the their information to the cloud.

2: The cloud collects sinks' reports and constructs the WDH and its incidence matrix specified by (8)(9).

(2) Iteration update

3: **Initially:** $t = 0$, $\pi_{i,k}(0) = \frac{1}{|\mathcal{A}_i+1|}$, $\forall i \in N, \forall k \in \mathcal{A}_i$

4: **Loop** $t = t + 1$

5: Randomly select one updating SN i, and marks each SN $l \in \mathcal{Z}_i$ and each SN $j \in \mathcal{J}_l$ as non-updating state. For those remaining unmarked SNs, successively perform the above operation until all SNs' states are determined.

6: The selected SNs update the strategy probability distribution $\boldsymbol{\pi}_i(t)$ as following:

$$\pi_{i,a_i(t-1)}(t) = \frac{\exp\left(\mu u_i\left(a_i(t-1), \boldsymbol{a}_{\mathcal{J}_i}(t-1)\right)\right)}{\sum_{a_i'\in\mathcal{A}_i} \exp\left(\mu u_i\left(a_i', \boldsymbol{a}_{\mathcal{J}_i}(t-1)\right)\right)} \tag{26}$$

where $\mu > 0$ is the learning parameter and $u_i\left(a_i(t-1), \boldsymbol{a}_{\mathcal{J}_i}(t-1)\right)$ is the utility function specified by (20).

7: The selected SNs choose a channel $a_i(t)$ according to $\boldsymbol{\pi}_i(t)$.

8: If $t < t_{\max}$, where $t_{\max}$ is the fixed maximum number of iteration set by cloud, the algorithm stops; otherwise, go to step 4.

9: **End Loop**

Generally, as shown in algorithm 1, the proposed algorithm includes two phases: hypergraph construct phase and iteration update phase. In the first phase, cloud formulates the interference relationship. In the second phase, multiple concurrent independent SNs update mixed strategy at each iteration in the cloud. In order to select multiple independent SNs, we mark SNs with state which indicate whether the SNs update their strategy probability distribution. The specific marking method is shown in step 5. For any two independent SNs i and j, the intersection of i's interfered SNs set and j's interfered SNs set is empty. That is, $\mathcal{Z}_i \cap \mathcal{Z}_j = \phi$. Note that the action of independent SNs won't affect each other's utility so that the WDH-based spectrum access algorithm can be seen as reformative SAP working in a concurrent manner. Similar to [20], we can easily prove that it has the same convergence property with SAP that if the learning parameter μ is sufficiently large, the WDH-based spectrum access algorithm can maximize sum of system EE and system SE with an arbitrarily high probability.

As we can see, the global optimization of EE and SE requires a large amount of information interaction between SNs. But learning algorithm is easy to be performed in the cloud with a limited cost. This centralized-distributed framework is practical in situations where energy and spectrum resources are scarce, because SNs don't carry on spectrum sensing and strategy learning. In reality, SNs access the spectrum according to the convergence result from cloud in each slot so that it has the advantages of powerful calculating ability and lower complexity requirements for sensors, which is crucial for wireless powered network.

It is hard solve complexity analysis problem in learning algorithm. Roughly speaking, one randomly selected SN calculates $C + 1$ available utility to update the strategy probability distribution in one iteration. Thus, for SAP,the time complexity is $O\left(t_{con}\left(C+1\right)\right)$, where t_{con} is the number of iterations before getting convergence. And for the WDH-based spectrum access algorithm, the time complexity is $O\left(t_{con}\left[M + M'\left(C+1\right)\right]\right)$ where M' is the number of independent SNs. Because in one iteration, the complex of independent SNs' selection is $O\left(M\right)$ and then M' SNs update their strategy probability distribution. Please note that the number of convergence iterations of the proposed algorithm is much smaller than SAP. Besides, in the clustered network with a large number of SNs, the WDH-based spectrum access algorithm requires less memory due to significant less hyperedge number compared with existing directed hypergraph.

V. SIMULATION RESULTS

We consider a simulation scenario consisting of 5 channels and 5 sinks with a transmission distance $r_T = 50m$ and an interference distance $r_I = 55m$. The locations of SNs, dedicated RF sources and PUs follow independent homogeneous Poisson point processes (HPPP) with different densities. The SN density and RF-source density in each transmitting zone are $\lambda_{SN} = 0.003\pi {r_T}^2 \approx 23.5619$ and $\lambda_{RF} = 0.00001\pi {r_T}^2 \approx 11.7810$, respectively, and the PU density in whole network is $\lambda_{PU} = 4$. The positions of SNs and PUs don't change until the end of once convergence. Besides, the rest of the simulation parameters are shown in Table 3.

In Fig. 5, we show the randomly generated network topology which follows the HPPP as mentioned above. In each convergence process, only the SNs locate in the harvesting zone of at least one RF source are active players which participate in spectrum allocation. Fig. 6 shows the interference relationship of SNs to sinks corresponding to Fig. 5.

In Fig. 7, we present a convergence process of the classic SAP algorithm and the proposed WDHG-based algorithm.

TABLE 3. Simulation parameters.

Slot duration	T	1 ms
Data transmitting duration	T_T	0.6 ms
Bandwidth	W	15kHz
Path loss exponent	α	4
Worst transmitting SINR	$\gamma_{\min}$	-10 dB
SN transmit power	P_T	1 mw
RF source transmit power	P_H	3 W
Noise power	N_0	-10 dBm
Energy harvesting efficiency	η	0.1
Average energy expended in data generating	β	5×10^{-6} J/bit
Data generating rate	v	5 bits/s

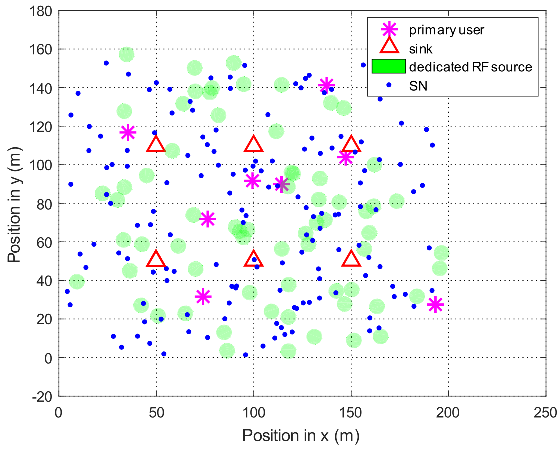


FIGURE 5. The randomly generated network topology which follows HPPP. The SN density and RF-source density in each transmitting zone are $\lambda_{SN} = 0.003\pi {r_T}^2 \approx 23.5619$ and $\lambda_{RF} = 0.00001\pi {r_T}^2 \approx 11.7810$, respectively, and the PU density in whole network is $\lambda_{PU} = 4$.

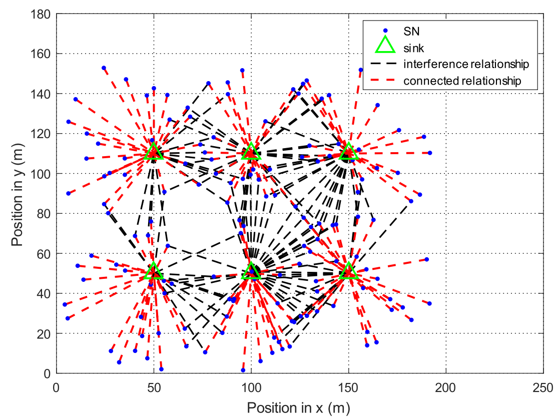


FIGURE 6. The interference relationships and connected relationships between SNs and sinks of the EH-CRSN topology in Fig. 5.

We can see that both SAP and the proposed algorithm can converge to the same level. And the proposed algorithm has a faster convergence speed than SAP.

The convergence behavior of the proposed WDHG-based algorithm is shown in Fig. 8, and we arbitrarily select 5 SNs as an example. At last, SN 1 and 5 access channel 5, SN 2 and 4 access channel 3, and SN 3 accesses channel 2. We can also see that, in one iteration, multiple SNs can update their strategies simultaneously.

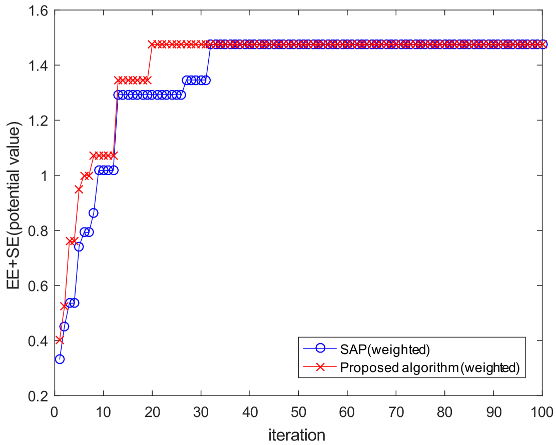


FIGURE 7. A convergence process of the classic SAP algorithm and the proposed WDHG-based algorithm.

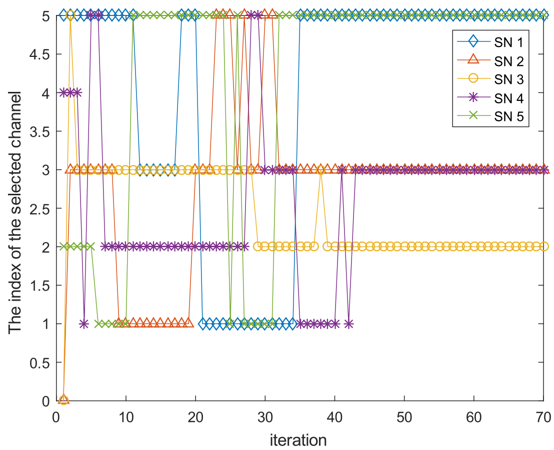


FIGURE 8. Partial SNs' strategy update in the learning process of the proposed WDHG-based algorithm.

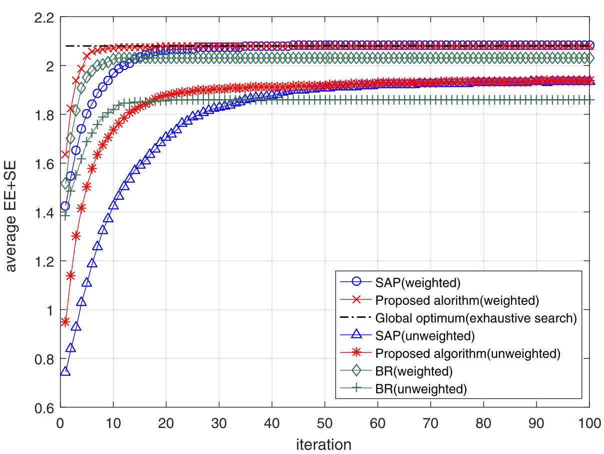


FIGURE 9. Average sum of system EE and SE versus iteration steps.

Since the irrelevant updating SNs are randomly selected in each iteration, the process of convergence is not the same each time. So we repeat the convergence 100 times in the same network topology and the convergence result averaged by 100 running samples is presented in Fig. 9. It shows the convergence process when best response (BR) [21], spatial adaptive play (SAP) and the proposed WDHG-based algorithm are used respectively. We can observe that using the WDH, compared with unweighted directed hypergraph, both SAP and the proposed WDHG-based algorithm can always converge to the sum of system EE and system SE consistent with the global optimum obtained by exhaustive search, while BR algorithm can only converge to the suboptimal result. This shows that the WDH game dose possess a PNE that maximizes the sum of system EE and system SE, which is consistent with Theorem 1. Besides,as we can see, the performance of the weighted directed hypergraph is better than that of the existing directed hypergraph. The reason is that the WDH fully considers the accurate interference degree. Thus, the spectrum allocation algorithms with WDH are more appropriate.

VI. CONCLUSION

In this paper, we investigated the spectrum access for cloud-assisted EH-CRSN to maximize the sum of system EE and SE. We gave the formula for EE and SE and proposed a WDH game for spectrum access. Then, we validated that NEs exist and we designed a WDHG-based spectrum access algorithm to converge to the optimal NE solution.

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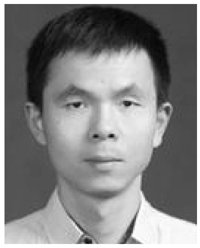

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