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An Energy Efficient Spectrum Sensing Algorithm in EH-HCRSN

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ABSTRACT In order to make up for the extra energy consumption caused by spectrum sensing and prolong the network lifetime, the energy harvesting (EH) module is introduced to the spectrum sensing nodes in cognitive radio sensor network (CRSN) and thus forms one new type of network: EH-aided node-heterogeneous CRSN. Take into account the fact that the existing spectrum sensing algorithms are difficult to be applied to the real practice (due to the high cost of algorithm implementation or network deployment) and may lead to the waste of channel and energy resources, an energy-efficient spectrum sensing algorithm is proposed in this paper. The proposed algorithm can maximize the energy utilization efficiency under the premise of detecting enough available time of channels, which is of great significance to reduce the network deployment cost and promote the green communication of wireless sensor network and even the large-scale deployment of Internet of Things applications. The simulation results demonstrate that the proposed algorithm can greatly improve the energy utilization efficiency of spectrum sensing nodes and channel utilization and significantly reduce the deployment cost of network equipments.

INDEX TERMS Cognitive radio sensor networks (CRSN), energy harvesting (EH), energy efficiency, spectrum sensing (SS), Internet of Things (IoT).

I. INTRODUCTION

The Internet of Things (IoT) is the evolution of Internet which is seizing a gigantic leap to collect, analyze and distribute data which can then turn it into information, eventually into an asset. The IoT is enabled by the latest developments in radio frequency identification (RFID), smart sensors, communication technologies, and Internet protocols [24]. Wireless sensor network (WSN) technology runs through all three levels (i.e. sensing, processing and communication) of the IoT, which has the advantages of large scale, low cost, high density, flexible deployment, real-time acquisition and all-weather work. It is an integrated application of the technologies in the three level, which is critical to the development of IoT. Therefore, studying WSN technology is extremely important for promoting the development of IoT applications, striving for the early realization of IoT visions, promoting the development of information industry economy and even the improvement of people's living standards.

Existing WSNs mainly operate on the industrial scientific medical (ISM) unlicensed spectrum band [1]. With the rapid development of emerging wireless communication technologies (such as Wifi, Bluetooth, Zigbee, etc.), the public frequency bands become increasingly crowded, and the interference among various wireless technologies also become increasingly serious.

In 2002, the spectrum policy task force (SPTF) investigated the use of spectrum resources and found that only about 15%-85% of wireless licensed spectrum was used in New York State, USA [19], and that most of the spectrum resources were not adequately utilized. The emergence of cognitive radio (CR) technology enables secondary users (SUs) to opportunistically access idle channels that are already licensed to primary users (PUs), thereby improving the efficiency of spectrum utilization and reducing interference among different users or technologies.

The introduction of CR technology in WSN is expected to effectively solve the mutual interference among various emerging technologies in the unlicensed spectrum band by opportunistically accessing idle channels licensed to PUs. The WSN whose nodes are equipped with CR devices is called cognitive radio sensor network (CRSN) [1]. In CRSN, spectrum sensing (SS) nodes need to frequently scan the spectrum to obtain high-resolution estimates of spectrum availability to avoid the interference between PUs and SUs [2]. However, such frequent scans greatly increase the energy consumption of traditionally energy-limited networks powered by batteries. Therefore, energy conservation technologies have become one of the research hotspots in CRSN area [9], [10].

Energy harvesting (EH) technology is regarded as one of the most promising schemes to address the energy consumption problem in CRSN [3]. Energy harvesting technology refers to the technology that effectively captures and collects ambient energy. The common energy harvesting sources includes solar, eolian, vibration [25], or man-made phenomena such as wireless node charging [26]. This technology has become a promising solution to achieve green communications, which can provide very long network lifetime and avoid manual battery recharging or replacement [27]. Sensor nodes equipped with EH modules/devices can harvest energy from other radio signals or environmental energy sources, and further run continuously without battery replenishment [4]. The CRSN equipped with EH modules is called energy harvesting aided CRSN (EH-CRSN). To reduce deployment costs, only the spectrum sensing (SS) nodes are equipped with EH modules to replenish the additional energy consumed by them while other sensor nodes are still powered by conventional batteries, thereby resulting in a new type of network: EH aided node-heterogeneous CRSN (EH-HCRSN) [6].

In EH-HCRSN, the continuous replenishable energy can greatly extend the network lifetime, thereby promoting the development of WSN applications. However, there are many differences between EH-HCRSN and the traditional CRSN in energy management. Firstly, in EH-HCRSN, the SS nodes need to periodically scan the spectrum, which leads to the more and faster energy consumption than that of the data sensor (DS) nodes. Secondly, the process of energy harvesting in the EH module is unstable, which leads to the fact that the SS schemes designed for traditional CRSN (the energy stored in the battery of nodes is static and stable) can not be applied to EH-HCRSN. Therefore, there is an urgent need for a new SS strategy in EH-HCRSN that can address the aforementioned two energy management problems.

A. RELATED WORK AND MOTIVATIONS

Existing SS strategies for energy management can be divided into two categories:

1) SS strategy without EH technology.
2) SS strategy with EH technology.

The first type of research work mainly focuses on how to improve the energy efficiency of SS. Due to the shadow effect, multipath effect and other interference, the detection accuracy of a single sensor node is difficult to satisfy requirement of SS [5]. The detection accuracy of cooperative SS can be enhanced by scheduling multiple nodes to simultaneously detect a channel [18], but it also increases the energy consumption at the same time. Reference [9] minimizes energy consumption by limiting the number of nodes involved in SS. In [10], some specific nodes are chosen to sense the spectrum, while other nodes are dormant to prolong the network lifetime. Reference [11] uses the karush-kuhn-tucker (KKT) condition in the optimization theory to find the sensors with the best detection performance for cooperative SS, and extend the network lifetime by balancing the residual energy among all SS nodes. However, balancing the energy consumption among the nodes can not maximize the network lifetime. To improve the energy efficiency in SS, a variety of performance parameters are optimized, such as the detection threshold of SS [13], sensing duration [14], and the channel switching cost [15]. The paper presents an architecture of CRSNs for IoT, in which sensor nodes can access the spectrum opportunistically and harvest energy from ambient radio-frequency sources. Reference [31] declares that the research on energy harvesting and cognitive radios (CRs) are vital for the success of Internet of Things (IoT). And it proposes an efficient KKT condition-based algorithm to determine the optimal packet size in CRSN. Reference [23] indicates CRSN is a promising solution for spectrum scarcity problem of IoT applications and proposes a novel channel access scheme to maximize system throughput. However, these SS strategies can not be applied to EH-HCRSN because they do not consider EH and the energy fluctuations caused by EH.

The second type of research work mainly focuses on how to deal with the contradiction between the unstable capability of energy harvesting and the continuous energy demand in the SS nodes, and how to detect as much available time of channels as possible for WSN. References [7] and [17] study the optimal cooperative sensing scheduling strategy that can select the optimal set of sensing nodes with the goal of maximizing the time average sensing utility. However, the references assumes the storage capacity of the battery in nodes to be infinite, which is inconsistent with the reality and further make the proposed algorithm difficult to be applied to the real practice (the increase in the storage capacity of the battery can lead to the rise in the cost of network deployment, so the capacity of the storage battery in nodes should be as small as possible under the premise of ensuring that the network can continuously operate). Reference [28] investigates the architecture and advantages of RF-powered CRSN, typical applications, as well as the key challenges arising from applying RF energy harvesting and transfer into CRSN. Meanwhile, it formulates a resource allocation framework to optimize network utility while guaranteeing network stability and sustainability. Reference [29] considers a cognitive radio system, in which a secondary transmitter harvests energy from a primary transmitter's wireless signals. And it proposes a two-level bisection search algorithm to achieve maximal secondary throughput. An energy and spectrum efficient scheme for CRSNs is proposed in [30]. Reference [6] studied the multichannel selection problem in SS. The proposed algorithm in the reference aims at maximizing the available time of channels detected by SS nodes. However, in real WSN, the maximum available time detected by the algorithm may not be fully utilized by DS nodes due to the lack of the consideration of the actual demand, which may cause the great waste of channel and energy resources. Moreover, in the literature, the energy harvesting rates in all SS nodes are assumed to be constant and identical, which is insistent with the fact that SS nodes at the different locations may have different energy harvesting probability/rate since energy source typically arrives randomly.

Besides the aforementioned problems, to the best of our knowledge, the implementation cost problem of algorithms is also not considered in the existing SS algorithms designed for EH-HCRSN, namely, the deployment cost of EH devices/modules is not still considered so far. More specifically, maximizing the available time or average time utility of channels in existing references [6]–[7], [17] may require EH devices to have a high energy harvesting and conversion rates to provide enough and continuous energy for SS nodes, thereby resulting in a sharp rise in the deployment cost of the nodes. Considering the fact that the energy harvesting and conversion rates of the current commercial EH devices are still very low, the existing SS algorithms are difficult to be applied to real practice.

Our work aim to propose an energy-efficient spectrum sensing algorithm (EESS), which can address the possible waste problem of channel and energy resources and the high implementation cost problem of SS algorithms (which make it difficult for the algorithms to be applied to real reality) in EH-HCRSN. At present, green communication is greatly advocated in communications industry, which aim to minimize the impact of the entire communication industry chain on the environment and maximize the resource efficiency. The proposed scheme can thus be regarded as one of enabling technologies for green communications.

More specifically, under the premise of ensuring the sensing performance and detecting enough available time of channels, with the consideration of the randomness of energy harvesting in EH devices, the proposed algorithm (EESS) can schedule SS nodes to detect the channels targeting the maximization of the available time detected by per unit energy consumption such that the channel scheduling scheme of SS with maximum energy utilization efficiency can be found, which can greatly reduce the network deployment cost and promote green communication of WSN. The novelty of the article is to consider the implementation cost problem of SS algorithms in EH-HCRSN and the time varying EH systems in SS nodes. The innovation will be detailed in the contribution section below.

B. CONTRIBUTIONS

The main contributions of this work can be summarized as follows:

- For the first time, the implementation cost problem of SS algorithms in EH-HCRSN, namely the deployment cost problem of the EH devices, is considered in this work. Different from the previous algorithms maximizing the detected available time or average time utility (which may lead to the waste of channel and energy resources and high deployment cost of EH devices), this work targets the maximization of the energy utilization efficiency (i.e. the available time detected by per unit energy consumption) and proposes an energy-efficient spectrum sensing algorithm. The proposed algorithm can not only avoid the waste of energy and channel resources in the previous algorithms, but also reduce the implementation cost of SS algorithms, which is in great value of practical application.
- For the first time, the actual demand of CRSN for the available time of channels in SS algorithms of EH-HCRSN is considered in this work. The constraint on the available time of channels detected by SS nodes is imposed in this work. It can enable the proposed algorithm to detect enough available time of channels for the data transmission of DS nodes when the energy utilization efficiency of SS nodes is maximized, which is of great significance to realize an energy-efficient SS algorithm.
- For the first time, the constraint on false alarm probability in SS algorithms of EH-HCRSN is considered in this work. It can make the false alarm probability of channels remain in the lower range and further improve the utilization of idle channels.
- For the first time, the time varying EH systems in SS nodes, which are modeled as independent Bernoulli processes with different probability, are considered in the EH-HCRSN system. It makes the developed algorithm in the paper more practical.

The remainder of this work is organized as follows. The network model is detailed in Section II. A mathematical formulation and the proposed solutions of the spectrum sensing problem are detailed in Section III. Performance evaluation results that demonstrate the efficiency of the proposed algorithms are presented in Section IV. Conclusions are drawn in Section V.

II. SYSTEM MODEL

A. CR MODEL

We consider the scenario of a single hop EH-HCRSN, which consists of three types of nodes: N battery-powered DS nodes, M EH-enabled SS nodes, and one sink node. It is shown in Fig. 1. The EH-HCRSN periodically operates over three phases: channel decision, SS and data transmission phase, as shown in Fig 2. In the phase of channel decision, based on some known information and certain spectrum sensing strategy, the channel allocation scheme to SS nodes can be determined for channel detection. In the second phase, based on the channel decision in the first phase, EH-enabled SS nodes cooperatively detect the licensed spectrum for idle channels. In the third phase, the available channels are utilized by DSs for data transmission. The sink node

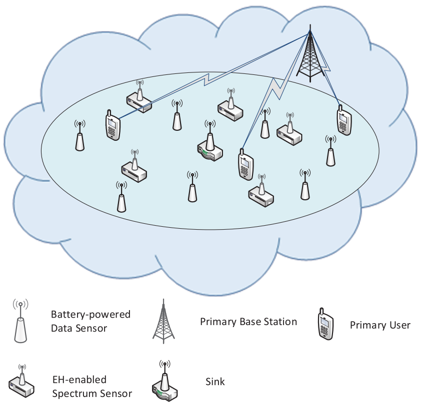

FIGURE 1. Illustration of an EH-HCRSN.

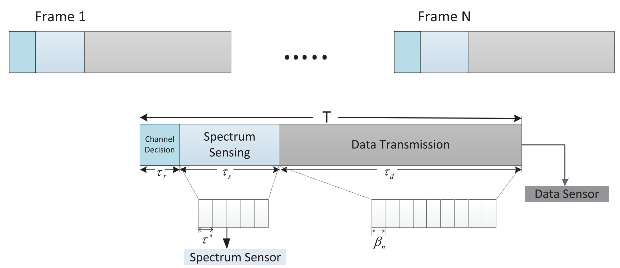

FIGURE 2. Timing diagram and frame structure of the EH-HCRSN.

is deployed at the network center as the fusion center of the entire network, and it can schedule SS nodes in the network to work cooperatively, including the cooperative sensing of SS nodes and data transmission of DSs.

In the paper, the duration of SS phase and data transmission phase are designed to be fixed, as shown in Fig. 2. Let τ_s and τ_d denotes the duration of SS phase and data transmission phase, respectively. Because the channel decision time τ_r is varied, the whole cycle T is dynamic. However, based on the existing hardware condition and the computation complexity of the spectrum sensing strategy, the channel decision time τ_r is often very small (e.g. less than 0.5ms for the proposed algorithm in the paper).

When a PU on a channel is detected, it means the channel is unavailable at this time. We use v_k to denote the transition rate from the unavailable state to the available state on the kth channel and u_k to denote the transition rate in the reverse direction [13]. The sampling frequency is denoted by f_s. The energy consumption and sensing time that one SS node detects one channel are denoted by e and τ', respectively.

We assume that the PU signal is a complex-valued phase-shift keying (PSK) signal and that the noise is circularly symmetric complex Gaussian with zero mean and σ^2 variance, then according to [16], the false alarm probability and the detection probability can be respectively calculated as

$$p_f(m,k) = \Pr(Y_{m,k} > \varepsilon \,|H_0) = Q((\frac{\varepsilon}{\sigma^2} - 1) \cdot \sqrt{f_s \cdot \tau'}) \quad (1)$$

$$p_d(m,k) = \Pr(Y_{m,k} > \varepsilon \,|H_1) = Q(\frac{Q^{-1}(\overline{p}_f) - \sqrt{f_s \cdot \tau'}}{\sqrt{2 \cdot \gamma_{m,k} + 1}} \quad (2)$$

where ε is the detection threshold of the energy detector, H_0 indicates that the target channel is not occupied by PUs, and H_1 indicates that the target channel is occupied by PUs. And $Y_{m,k} = (1/U)\sum_{u=1}^{U} \left|y_{m,k}(u)\right|^2$ denotes the output of the energy detector which is taken to decide on the state of the PU, i.e., the test statistic [6]. $U = f_s \cdot \tau'$ is the number of samples, $y_{m,k}(u)$ is the uth sample of the received signal at the mth spectrum sensor on the kth channel. If the output of the energy detector exceeds ε, the PU is considered as being on the channel, i.e., the channel is unavailable. $\gamma_{m,k}$ denotes the received Signal to Noise Ratio (SNR) from the PU on the kth channel. In the paper, the detection threshold is designed to be the same for all of the spectrum sensors, the false alarm probability thus becomes fixed for all of the sensors and is denoted by $\overline{p}_f$.

SS nodes make a binary assessment on each target channel according to the SS result, and then the binary decisions are sent to the sink node for data fusion following the logic-OR rule [10]. The common fusion methods are the logic-OR rule, the logic-AND rule, the K-out-of-N rule and so on. Currently the most widely applied method is the logic-OR rule [15], which is a criterion biased toward reducing interference to PUs. If at least one sensing result exceeds the threshold ε (i.e., the decision result of at least one SS node is 1), the channel is regarded as being unavailable, i.e., there is a PU on the channel. Therefore, the final false-alarm probability Q_{f}^k and final detection probability Q_{d}^k can be written as follows [6]:

$$Q_{\mathrm{f}}^k = 1 - \prod_{m \in M_k} (1 - p_f) \quad (3)$$

$$Q_{\mathrm{d}}^k = 1 - \prod_{m \in M_k} (1 - p_d) \quad (4)$$

where M_k represents the number of SS nodes that is scheduled to detect the kth channel.

B. EH MODEL

In the paper, each SS node is assumed to be equipped with a rechargeable battery with finite capacity. The battery with finite capacity can guarantee the sustainability of the power when the SS nodes don't harvest energy in some time. We assume that the energy arrives randomly at the EH-enabled SS nodes in each cycle T. As described in previous section, the channel decision time τ_r is very small, the differences among the channel decision time in different work cycles is smaller. We can thus assume the arrival process of the energy in the SS nodes to be independent Bernoull process with the probability of $\lambda_m (m \in 1, 2, \ldots, M)$ in a cycle. We also assume that the mth SS node can harvest energy e_h^m with the probability λ_m in a cycle. The Bernoulli model is simple, but it captures the random and sporadic availability of ambient energy source [5]. In practice, statistics of the energy harvesting models are time varying. However they can be approximated by piecewise stationary processes [5], and the Bernoulli model has this property.

III. CROSS-ENTROPY BASED SPECTRUM SENSING ALGORITHM

The Cross-Entropy (C-E) algorithm is an algorithm that can find the optimal solution in combinatorial and continuous nonconvex optimization problem with convex bounded domains [21]. Its basic idea is to transform a deterministic optimization problem to an Associated Stochastic Problem (ASP) problem that can be easily solved [21], [22]. More specifically, the C-E algorithm is an adaptive algorithm, which can produce a series of stochastic solutions converging to or approaching the optimal solution of the original deterministic problem.

Based on the idea of C-E algorithm, we aim to find the channel allocation scheme for SS with the highest energy utilization efficiency through multiple iterations, while satisfying the following constraint conditions:

1) The detected actual available time can not be less than the transmission time required by the DSs.
2) The interference to PUs can not exceed the predefined threshold.
3) The false alarm probability of the channels cannot be higher than the predefined threshold.
4) The energy consumption rate of SS nodes can not exceed the energy harvesting rate of the EH module to meet the demand for the energy sustainability of SS nodes.
5) The sensing time for a single channel can not exceed τ_s.

Based on the priori information of channel k, the mean sojourn time of the available state and the unavailable state on the channel can be calculated as $L_0^k = 1/u_k$ and $L_1^k = 1/v_k$, respectively. According to the stochastic process theory, the stationary probabilities of the available and unavailable states can respectively be given by [6]

$$p_0^k = \frac{v_k}{u_k + v_k} \tag{5}$$

$$p_1^k = \frac{u_k}{u_k + v_k} \tag{6}$$

The average available time on the channel k can thus be given by [6]

$$\overline{\partial^{\mathrm{k}}} = L_0^k \cdot p_0^k \tag{7}$$

Let J denote a matrix with M rows and K columns, where the row denotes node number and the column denotes channel number. In matrix J, the element $[\mathbf{J}]_{m,k}$ indicates whether the mth SS node participates in the detection of the kth channel. The value 1 means that the mth SS node participates in the detection of the kth channel, and the value 0 means not.

Let p_{avail}^k denote the probability that channel k can be detected to be available given that channel k is idle, then it can be written as [6]:

$$p_{avail}^k = 1 - Q_f^k = \prod_{m \in M_k} (1 - p_f) = (1 - p_f)^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}} \tag{8}$$

The total available time of channels detected by SS nodes can thus be represented as [6]:

$$t_d = \sum\nolimits_{k=1}^{K} \overline{\partial^k} p_{avail}^k I_d^k = \sum\nolimits_{k=1}^{K} \overline{\partial^k} (1 - p_f)^{\sum_{m=1}^{M} [\mathbf{J}]_{m,k}} I_d^k \tag{9}$$

where I_d^k is a binary variable.

The binary variable I_d^k introduced in the formula (9) indicates whether the protection requirement of PUs, i.e. the second constraint condition, is satisfied or not, which can thus be given by [6]

$$I_d^k = \begin{cases} 1 & 1 - Q_d^k < Thr \\ 0 & 1 - Q_d^k \geq Thr \end{cases} \tag{10}$$

where Thr is the predefined misdetection probability threshold. According to equation (4), $1 - Q_{\mathrm{d}}^k$ indicates the final misdetection probability of channel k. If $1 - Q_{\mathrm{d}}^k$ exceeds Thr, the detection of the channel k is considered as being unreliable, and the channel k can not be accessed by DSs. Otherwise, the channel can be accessed.

It is not hard to understand that the longer the occupancy time on the channel by DSs is, the more likely it is to collide with PUs. In order to keep the collision probability as low as possible on the channel, it is necessary to control the occupancy time on each channel by DSs. We use $\partial_{\max}^k$ to denote the maximum occupancy time on the kth channel. Obviously, $\partial_{\max}^k \leq \overline{\partial^k}$.

The PU behavior on each channel can be modeled as a stationary exponential ON-OFF random process [8], then the probability of collision on the kth channel can be given by [6]:

$$p_{coll}^k(\overline{\partial^k}) = p_0^k \cdot (1 - e^{-\mu_k \overline{\partial^k}}) \tag{11}$$

where p_0^k is the probability that the PU is not present on the kth channel at the beginning of the data transmission phase, and $1 - e^{-\mu_k \overline{\partial^k}}$ is the probability that the PU returns the k channel in $[0, \overline{\partial^k}]$.

Assuming that the collision probability of channel k is required not to be greater than the predefined threshold $\overline{p_{coll}^k}$, from formula (11), we can obtain [6]

$$\overline{\partial^k} \leq \frac{-\ln(1 - \overline{p_{coll}^k}/p_0^{\mathrm{k}})}{\mu_k} \tag{12}$$

Considering $\partial_{\max}^k \leq \overline{\partial^k}$, the maximum occupancy time on the kth channel by DSs should satisfy the following constraint condition [6]:

$$\partial_{max}^k \leq \frac{-\ln(1 - \overline{p_{coll}^k}/p_0^{\mathrm{k}})}{\mu_k} \tag{13}$$

Additionally, $\partial_{\max}^k$ can not exceed the data transmission phase τ_d, $\partial_{\max}^k$ can thus be given by [6]:

$$\partial_{\max}^k = \min\left(\frac{-\ln(1 - \overline{p_{coll}^k}/p_0^{\mathrm{k}})}{\mu_k}, \tau_d \right) \tag{14}$$

Therefore, the detected available time of all channels for DSs transmission can be determined by:

$$t_{access} = \sum_{k=1}^{K} \partial_{\max}^{k} I\left(\sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k} > 0\right) \tag{15}$$

where $I\left(\sum_{m=1}^{M} [\mathbf{J}]_{m,k} > 0\right)$ is a binary variable introduced to indicate whether the kth channel is detected, the indicator function $I(\bullet)$ takes the value of 1 for true evaluations and zero otherwise.

According to the constraint condition (1), the proposed algorithm needs to ensure that the detected available time can meet the demand for the transmission time of DSs, the constraint can thus be represented as:

$$t_{access} \geq N\beta \tag{16}$$

where N is the number of DS nodes in the network, and β is the average transmission time required by DSs.

In this work, we intend to maximize the energy utilization efficiency, i.e. the available time of channels detected by each unit of energy consumption, which can be described as

$$\max_{\mathbf{J}} \frac{\sum_{k=1}^{K} \overline{\partial^{k}} (1-p_f)^{\sum\limits_{m=1}^{M} [\mathbf{J}]_{m,k}} I_d^k}{\left(\sum_{m=1}^{M} \sum_{k=1}^{K} [\mathbf{J}]_{m,k}\right) \cdot \mathrm{e}} \tag{17}$$

In order to improve the channel utilization efficiency, the false alarm probability of channels should remain within a certain range, thus we impose the constraint (3) on it, which can be given by

$$Q_f^k \leq \alpha, \quad \forall k \tag{18}$$

where α is the predefined threshold of the false alarm probability.

Associating (8) with (18), we can get

$$(\sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k}) \leq \frac{\ln(1-\alpha)}{\ln(1-p_f)}, \quad \forall k \tag{19}$$

Rounding down the right part of the formula (19) can obtain

$$(\sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k}) \leq \left\lfloor \frac{\ln(1-\alpha)}{\ln(1-p_f)} \right\rfloor = \Psi, \quad \forall k \tag{20}$$

According to the constraint (5), the total sensing time of one channel can not exceed the duration of the SS phase, i.e.,

$$\sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k} \tau' \leq \tau_s, \quad \forall k \tag{21}$$

Let N_{slot} denote the number of sensing time slots in the SS phase, then $N_{slot} = {}^{\tau_s}/_{\tau'}$, and further formula (21) can be described as

$$\sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k} \leq N_{slot}, \quad \forall k \tag{22}$$

In a sensing time slot, a SS node can only sense a single channel, thus the number of channels detected by a SS node can not exceed the total number of sensing time slots, i.e.,

$$\sum\nolimits_{k=1}^{K} [\mathbf{J}]_{m,k} \leq N_{slot}, \quad \forall m \tag{23}$$

In order to ensure the energy sustainability of each SS node, the energy consumption of each SS node should not exceed the energy harvested by itself in each work cycle, i.e.,

$$\left(\sum\nolimits_{k=1}^{K} [\mathbf{J}]_{m,k}\right) \cdot \mathrm{e} \leq E_m, \quad \forall m \tag{24}$$

where $E_m = e_h^m \cdot \lambda_m$ is the energy harvested by the EH module in SS nodes during the work cycle T.

Therefore, the optimization problem of the energy utilization efficiency with the consideration of multiple constraints in the multi-channel scenario can be expressed as

$$\max_{\mathbf{J}} \frac{\sum_{k=1}^{K} \overline{\partial^{k}} (1-p_f)^{\sum\limits_{m=1}^{M} [\mathbf{J}]_{m,k}} I_d^k}{\left(\sum_{m=1}^{M} \sum_{k=1}^{K} [\mathbf{J}]_{m,k}\right) \cdot \mathrm{e}}$$

$$\text{s.t.} \begin{cases} t_{access} \geq N\beta, & \forall m \\ \left(\sum\nolimits_{k=1}^{K} [\mathbf{J}]_{m,k}\right) \cdot \mathrm{e} \leq E_m, & \forall m \\ \sum\nolimits_{m=1}^{M} [\mathbf{J}]_{m,k} \leq N_{slot}, & \forall k \\ \sum\nolimits_{\mathrm{k}=1}^{K} [\mathbf{J}]_{m,k} \leq N_{slot}, & \forall m \\ [\mathbf{J}]_{m,k} = \{0,1\}, & \forall m,k \\ Q_f^k \leq \alpha, & \forall k \end{cases}$$

where $\sum_{m=1}^{M} [\mathbf{J}]_{m,k}$ in the objective function represents the number of SS nodes that are scheduled to detect the kth channel.

When the number of the SS nodes scheduled to detect channel k increases, according to formula (8) the probability p_{avail}^k decreases, and according to the equation (4) and the formula (10) I_d^k tends to take the value of 1 (i.e. the detection probability Q_d^k of channel k increases). On the contrary, when the number of SS nodes scheduled to detect channel k deceases, I_d^k tends to take the value of 0 (i.e. the detection probability Q_d^k of channel k decreases). Therefore, we can concluded that there is an optimal tradeoff in the number of SS nodes scheduled to sense channels (or between p_{avail}^k and I_d^k). However, the optimization problem is an integer programming problem.

Intuitively, the objective function in (17) can be optimized by executing an exhaustive search over the space defined by the constraints. However, this scheme leads to a search space of size 2^{MK}, which is computationally prohibitive, particularly for the resource-limited sensor network. Although the performance bound of the C-E algorithm remains an open theoretical issue [22], it has been shown effective in solving a similar combinatorial optimization problem [6], [12]. Therefore, in this work, the C-E algorithm [21] is employed to address the optimization problem.

By employing a penalty method, the constrained problem can be transformed into an unconstrained problem, which can be expressed as

$$O = \frac{\sum_{k=1}^{K} \overline{\partial^k}(1-p_f)^{\sum_{m=1}^{M}[\mathbf{J}]_{m,k}} \cdot I_d^k}{\left(\sum_{m=1}^{M}\sum_{k=1}^{K}[\mathbf{J}]_{m,k}\right)\cdot \mathrm{e}} - w\cdot I_1 - w\cdot I_2 - w\cdot I_3 - w\cdot I_4 - w\cdot I_5 \tag{25}$$

$$I_1 = I(t_{access} < N\beta) \tag{26}$$

$$I_2 = I\left(\sum_{k=1}^{K}[\mathbf{J}]_{m,k}\cdot \mathrm{e} > E_m\right) \tag{27}$$

$$I_3 = I\left(\sum_{m=1}^{M}[\mathbf{J}]_{m,k} > N_{slot}\right) \tag{28}$$

$$I_4 = I\left(\sum_{k=1}^{K}[\mathbf{J}]_{m,k} > N_{slot}\right) \tag{29}$$

$$I_5 = I\left(Q_f^k > \alpha\right) = I\left(\sum_{\mathrm{m}=1}^{M}[\mathbf{J}]_{m,k} > \Psi\right) \tag{30}$$

where $w = \sum_{k=1}^{K}\overline{\partial^k}$ is the penalty for violating any of the constraints.

The value of the indicator function $I(\bullet)$ is 1 when the decision in the brackets is true and zero otherwise. This penalty mechanism allows the channel assignment schemes satisfying the constraints to obtain higher priority value. This means that the schemes have the priority to be chosen in sorting. The new round of probability matrix can be generated by these excellent samples, through which the better samples can then be found. The sample schemes with poor performance because of not meeting the penalty conditions are abandoned, namely, they do not participate in generating a new round of probability matrix.

For a single user, there are 2^K kinds of selection algorithms in choosing channels during the entire SS phase. If these algorithms are numbered and each number only corresponds to one algorithm, the set of the number of these algorithms is a 1×2^K one-dimensional matrix, denoted by C. A binary matrix $\mathbf{V}^{\mathrm{z}} = \{v_{m,c}^{z} | 1 \le m \le \mathrm{M}, c \in \mathrm{C}\}$ with M rows and K columns, whose elements are 0 or 1, is defined for the convenient selection of the allocation algorithms. Its superscript z is introduced to denote the sample number. The value 1 of the element (m, c) means that node m adopts algorithm c. In matrix V^z, the sum of any row is 1, i.e. each node can only select one algorithm at a time.

Let $\mathbf{Q}^i = \{q_{m,c}^i | 1 \le m \le M, c \in C\}$ denote the probability matrix, where the element $q_{m,c}^i$ represents the probability of SS node m adopting algorithm c, and i is the number of iterations in the optimization. Therefore, the optimization steps of the proposed EESS algorithm are summarized as follows.

Algorithm 1 The C-E Based EESS Algorithm

Input:
The counter of iterations i
The maximum number of iterations i_{max}
The probability matrix Q^1;
The threshold of iteration termination ζ.

Output:
The probability matrix Q^i.

1: Initialize the counter of iterations $i = 1$;
2: Initialize the maximum number of iterations $i_{\max}$;
3: Initialize the elements in the probability matrix Q^1 to be a uniform distribution such that SS node m chooses vector c with probability $q_{m,c}^1 = 1/|C|, \forall m, c$.
4: **repeat**
5: Randomly generate Z samples of the matrix $\mathbf{V}^z$ based on the matrix Q;
6: Substitute the Z samples into the object function (25) and obtain an objective function value O_Z for each sample, sort the Z values of O_Z in descending order and select W optimal samples;
7: Update the new probability matrix Q according to the following formula:

$$q_{m,c}^{i+1} = \frac{\sum_{z=1}^{W} v_{m,\mathrm{c}}^{z}}{W} \tag{31}$$

8: **until**

$$\left\|\mathbf{Q}^{i+1} - \mathbf{Q}^{i}\right\|_{Fr} \le \zeta \quad \text{or} \quad i \ge i_{max} \tag{32}$$

Equation (32) represents the Frobenius norm, i.e., the sum of the squares of each element in the matrix. When the iteration stops, the solution $\mathbf{V}^z$ with the maximum value of objective function O_Z is selected, and the corresponding matrix $\mathbf{J}$ can be obtained and regarded as the optimal channel allocation scheme. In the above algorithm, each iteration is a periodic optimization. As the number of iterations increases, the matrix Q increasingly approaches the optimal value until the trend of the matrix is flat enough. When the iteration stops, the optimal allocation scheme can be obtained from the sample value at this time.

IV. PERFORMANCE EVALUATION

We assume that there are 10 SS nodes and 30 DS nodes in the considered EH-HCRSN, and they are uniformly distributed in a circular area with a radius of 20m. The sink node is located in the center of the circular area, and there are totally 7 licensed channels. The parameters for numerical simulations are shown in Table 1, and the prior information of the licensed channels is shown in Table 2.

As discussed above, [6] also proposed a spectrum sensing algorithm to schedule SS nodes to sense channels in EH-HCRSN, the proposed algorithm (EESS) in the paper is thus compared with the proposed algorithm in the reference for the performance evaluation. For convenient description, the proposed algorithm in the reference is also referred to as Time-maximum SS (TMSS) in this work.

In order to further understand the proposed algorithm (EESS), we compare it with the exhaustive method, the random assignment and TMSS in a network with 3 SS nodes, 10 DS nodes and 2 to 4 licensed channels. The exhaustive method searches all possible allocation schemes and find

TABLE 1. The key notations.

Notation	Definition
T	The work cycle
τ_s	The duration of SS phase
τ_d	The duration of data transmission phase
τ_r	The channel decision time
τ'	Sensing time that one SS node senses one channel
e	Energy consumption when one SS node detects one channel
f_s	The sampling frequency
Q_{f}^k	The final false-alarm probability
Q_{d}^k	The final detection probability
v_k	The transition rate from the unavailable state to the available state on the kth channel
u_k	The transition rate from the available state to the unavailable state on the kth channel
$Y_{m,k}$	The output of the energy detector
p_0^k	The stationary probabilities of the available states of the kth channel
p_1^k	The stationary probabilities of the unavailable states of the kth channel
$\overline{\partial^{\mathrm{k}}}$	The average available time on the kth channel
p_{avail}^k	The probability that channel k can be detected to be available given that channel k is idle
t_d	The total available time of channels detected by SS nodes
L_0^k	The mean sojourn time of the available state on the kth channel
L_1^k	The mean sojourn time of the unavailable state on the kth channel
t_d	The total available time of channels detected by SS nodes
$\partial_{\max}^k$	The maximum occupancy time on the kth channel
$\overline{p_{coll}^k}$	The predefined collision probability threshold
t_{access}	The detected available time of all channels for DSs transmission
I_d^k	The binary variable indicates whether the protection requirement of PUs is satisfied or not
Thr	The predefined misdetection probability threshold
$[\mathbf{J}]_{m,k}$	The binary element indicates whether the mth SS node participates in the detection of the kth channel
E_m	The energy harvested by the EH module in SS nodes during the work cycle T
Q^i	The probability matrix
$q_{m,c}^i$	The probability of SS node m adopting algorithm c
V^z	A binary matrix defined for the convenient selection of the allocation algorithms

TABLE 2. Parameter setting.

Parameter	Setting
False alarm probability	$\overline{p}_f = 0.1$
False alarm probability threshold	$\alpha = 0.3$
Collision probability threshold	$\overline{p_{coll}^k} = 0.1$
Termination threshold of the iterations	$\zeta = 10^{-3}$
Sensing time that one SS node senses one channel	$\tau' = 10^{-3}s$
Energy consumption when one SS node detects one channel	$\mathrm{e} = 0.11 \times 10^{-3}J$
Bernoulli mean	$\lambda_m \in [0.5, 0.9]$
Duration of the SS phase	$\tau_s = 5 \times 10^{-3}s$
Duration of the data transmission	$\tau_d = 95 \times 10^{-3}s$

TABLE 3. The prior information of the licensed channels.

k	1	2	3	4	5	6	7
v_k	0.6	0.8	1	1.2	1.4	1.6	1.8
u_k	0.4	0.8	0.6	1.6	1.2	1.4	1.8

the optimal solution from them, while the random allocation scheme randomly allocates the channels to the SS nodes. The prior information of the licensed channels uses the information of the first to fourth channel in Table 1. Simulation parameters are $Thr = 0.1$, $e_h^m = 0.6mJ$, $\beta = 5ms$. Their performance comparison is shown in Fig. 3. It can be seen from Fig. 3 that the energy utilization efficiency of the exhaustive method is the highest, while that of the random assignment is the lowest. The energy utilization efficiency of the proposed algorithm (EESS) can reach 77%-94% of that of the exhaustive method, while that of TMSS can only reach 57%-66%. It can be seen from Fig. 3 that as the number of channels increases, the energy utilization efficiency of EESS increasingly approaches the exhaustive method that can be regarded as being the optimal solution in energy utilization efficiency. However, the computation complexity of the exhaustive method is $O(2^{MK})$, which is computationally prohibitive, while that of the EESS algorithm is $O(MW2^K)$.

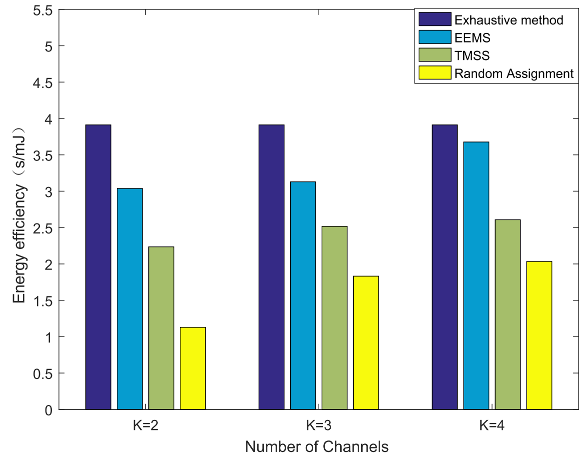

FIGURE 3. The comparison of the energy efficiency of different algorithms.

Fig. 4 and Fig. 5 respectively depicts the energy utilization efficiency (the available time detected by per unit of energy consumption) of the proposed algorithm (EESS) and TMSS, and in Fig. 4 and 5, the prior information of the licensed channels uses the information of the first to sixth channel in Table 1.

Fig. 4 shows the comparison of energy utilization efficiency of EESS algorithm under different misdetection thresholds. It can be seen from Fig. 4 that the energy utilization efficiency fluctuates at the beginning of the iteration. This is because the sample of the channel assignment vector is uniformly distributed in the initial stage of the proposed C-E algorithm. With the execution of the algorithm/iteraion, the probability of generating samples with high energy efficiency is getting higher and higher, and finally the algorithm converges to a stable solution. It can be observed from the Fig. 4 that the energy utilization efficiency decreases when the misdetection threshold Thr decreases. This is because more SS nodes may be required to participate in channel detection to improve the detection probability of the channel when the misdetection threshold Thr decreases. The more SS nodes participate in channel detection, the more energy is consumed and the less available time is detected, according

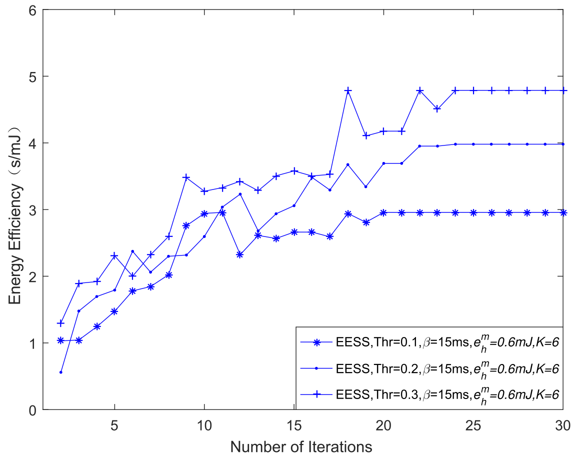

FIGURE 4. The comparison of energy efficiency of EESS algorithm with different misdetection threshold.

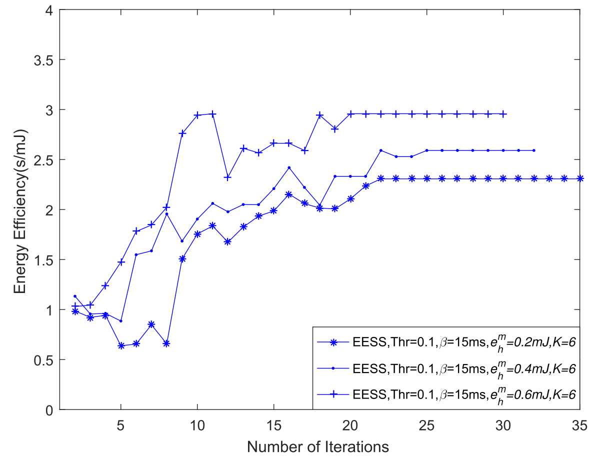

FIGURE 6. The comparison of energy efficiency of EESS algorithm under different e_h^m.

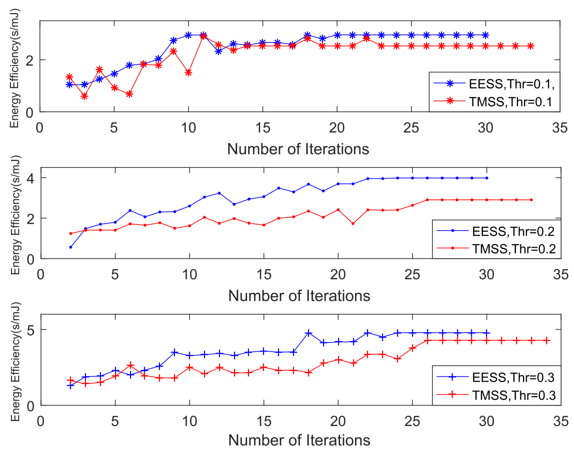

FIGURE 5. The comparison of the energy efficiency of the two algorithms under different misdetection threshold.

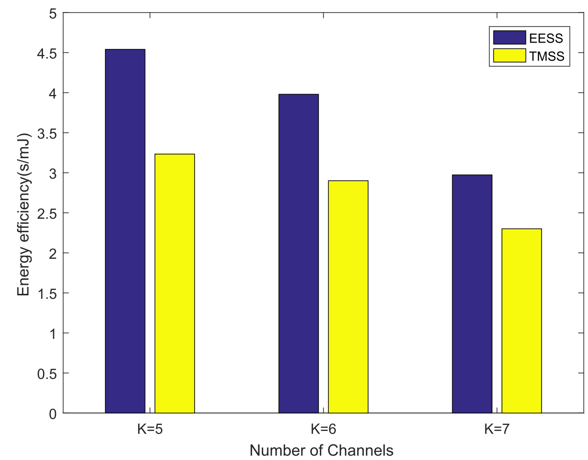

FIGURE 7. The comparison of the energy efficiency of the two algorithms under different number of channels.

to the formula (9). Finally it leads to the the decrease of the energy efficiency.

Fig. 5 shows the comparison of the energy utilization efficiency of EESS and TMSS under different misdetection thresholds. It can be seen from Fig. 5 that the convergence speed of EESS algorithm is faster than that of TMSS algorithm, and the energy utilization efficiency of EESS algorithm is always higher than that of TMSS algorithm. This is because TMSS aims at maximizing the available time of channels (ignoring the energy utilization efficiency of SS nodes), while the proposed algorithm (EESS) aims at maximizing the energy utilization efficiency, namely, the available time detected by per unit of energy consumption.

Fig. 6 shows the convergence and energy efficiency of EESS algorithm under different e_h^m. When the harvested energy e_h^m decreases, the energy utilization efficiency also decreases. This is because when the EH capability of the sensor is reduced, the number of channels it can detected is also reduced in the SS phase. This may result in insufficient nodes participating in the channel detection, which causes a decrease in the final detection probability Q_d^k of the channel according to the equation (4), and further lead to the under-utilization of these channels. Thus it decreases the channel available time detected by nodes and the energy utilization efficiency.

Fig. 7-10 show the simulation results under $M = 10$, $\beta = 15ms$, $e_h^m = 0.6mJ$, $Thr = 0.2$. Fig. 7 depicts the energy utilization efficiency (the available time detected by per unit of energy consumption) of the proposed algorithm (EESS) and TMSS for different number of channels. It can be observed from Fig. 7 that the energy utilization efficiency of the TMSS algorithm is about 30%-40% higher than that of the TMSS algorithm under the same channels. We can also note from Fig. 7 that the energy utilization efficiency becomes smaller and smaller when the number of channels grows. This is because the average available time of the added channels is smaller and smaller (as can be observed from the formula (7) and the prior information in Table 1. Obviously, if the prior information of all channels is same, the energy utilization efficiency would remain constant).

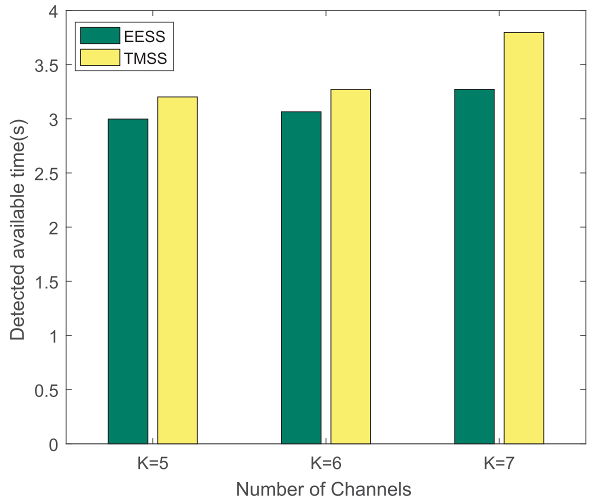

FIGURE 8. The comparison of total available time under different numbers of channels.

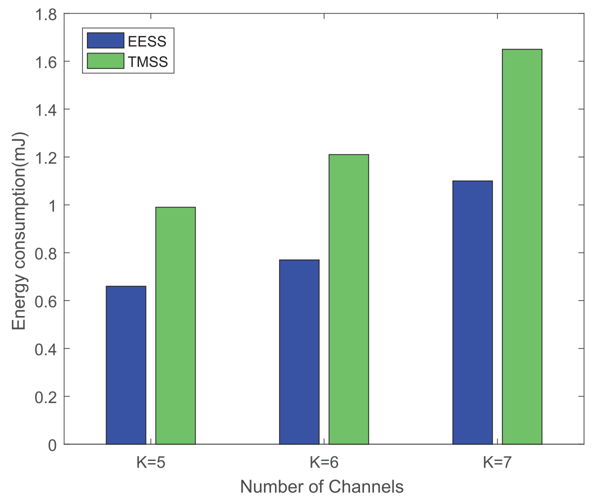

FIGURE 9. The comparison of the energy consumption under different numbers of channels.

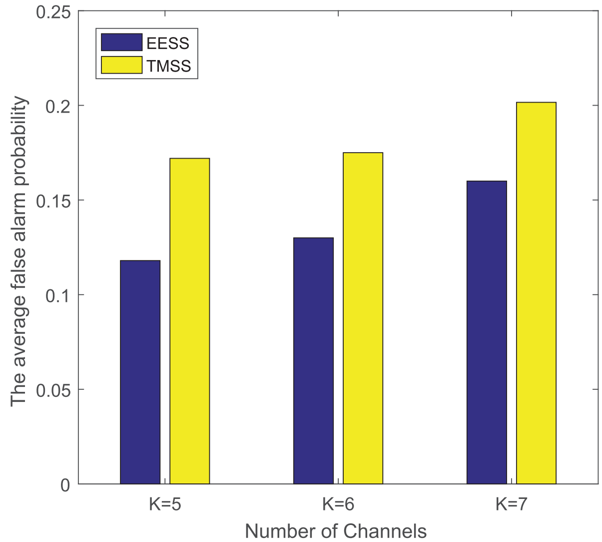

FIGURE 10. The comparison of the average false alarm probability under different numbers of channels.

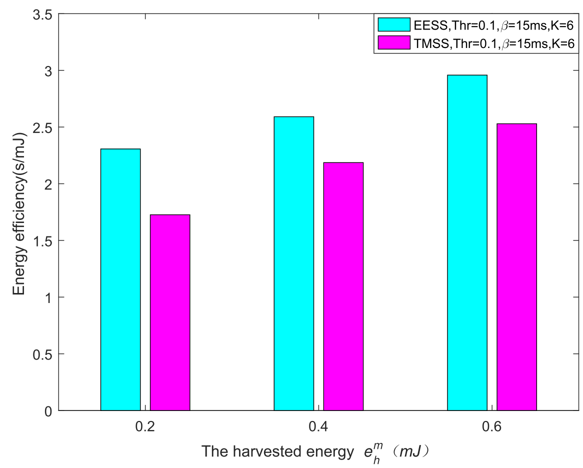

FIGURE 11. The comparison of the energy efficiency under the same e_h^m.

Fig. 8 shows the comparison of total available time detected by the two algorithms under different number of channels. The total time detected by the EESS algorithm can reach 86%-93.6% of the total time detected by the TMSS algorithm. However, the detected available time by TMSS may not be fully utilized since TMSS does not considering the actual demand of DS nodes, which may result in the waste of valuable channel and energy resources. It can be seen from Fig. 9 that the energy consumption of the EESS algorithm is much smaller than that of the TMSS algorithm, which is only equivalent to 63.6%-66.7% of the TMSS algorithm. This leads to the fact that the proposed algorithm (EESS) can be significantly better than TMSS in energy utilization efficiency, as shown in Fig. 7.

Fig. 10 shows the comparison of the average false alarm probability of channels under different number of channels. We can see from the diagram that the average channel false alarm probability of EESS is reduced by 20.6%-31.4% compared with TMSS, which improves the utilization efficiency of idle channels. This is because the proposed algorithm (EESS) takes into account the constraint on the false alarm probability, thereby controlling the false alarm probability of EESS, while TMSS ignores this.

Fig. 11 shows the comparison of the energy utilization efficiency of the two algorithms under the same e_h^m. It can be observed from Fig. 11 that under the same e_h^m, the energy utilization efficiency of EESS is always much higher than that of TMSS. This means that the lower energy harvested is required in the proposed algorithm (EESS) to obtain the same energy utilization efficiency as that of TMSS. This also leads to the lower implementation cost of the algorithm (i.e. the deployment cost of EH devices), which is extremely important for WSNs, especially in the case that the current EH technology is not yet mature.

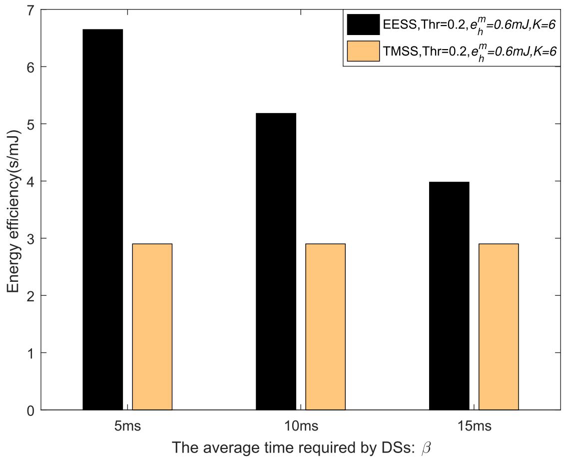

FIGURE 12. **The comparison of energy efficiency of each algorithm under the same β.**

It can be observed from Fig. 12 that under the same average transmission time β, the energy utilization efficiency of EESS is always larger than that of TMSS. This is because the proposed algorithm (EESS) maximizes the energy utilization efficiency under the premise of detecting enough available time of channels, while TMSS only maximizes the available time of channels. Since TMSS does not take into account the actual available time of DS nodes, its energy utilization efficiency is not affected by the average transmission time β and is constant, as shown in Fig. 12. It can be also observed from Fig. 12 that the energy utilization efficiency of our algorithm (EESS) increases with the decrease of β. This is because the constraint (16) becomes looser and looser when β decreases, and further the idle channel is detected more easily.

V. CONCLUSION

An energy-efficient spectrum sensing (EESS) algorithm is proposed in this work. The algorithm can address the problem that existing SS algorithms are difficult to be applied to real practice (due to the high cost of algorithm implementation or network deployment) and avoid the possible waste of channel and energy resources. The proposed algorithm (EESS) can maximize the efficiency of energy utilization on the premise of ensuring the sensing performance and detecting enough available time of channels, which can greatly reduce the network deployment cost (i.e. the deployment cost of EH devices), promote the green communication and the large-scale deployment of IoT applications. Extensive simulation results have demonstrated that the proposed algorithm can make full use of the precious energy harvested by SS nodes, thereby greatly improving the energy utilization efficiency and reducing the network deployment cost.

REFERENCES

[1] F. Akyildiz *et al.*, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] C. C. Chang and H. Y. Lin, "Spectrum reconstruction for on-chip spectrum sensor array using a novel blind nonuniformity correction method," *IEEE Sensors J.*, vol. 12, no. 8, pp. 2586–2592, Aug. 2012.

[3] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embedded Comput. Syst.*, vol. 6, no. 4, p. 32, 2007.

[4] Y. Zhang, S. He, and J. Chen, "Data gathering optimization by dynamic sensing and routing in rechargeable sensor networks," *IEEE/ACM Trans. Netw.*, vol. 24, no. 3, pp. 1632–1646, Jun. 2016.

[5] N. Pappas, J. Jeon, A. Ephremides, and A. Traganitis, "Optimal utilization of a cognitive shared channel with a rechargeable primary source node," *J. Commun. Netw.*, vol. 14, no. 2, pp. 162–168, 2012.

[6] D. Zhang *et al.*, "Energy-harvesting-aided spectrum sensing and data transmission in heterogeneous cognitive radio sensor network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 831–843, Jan. 2017.

[7] J. Yang, "Optimal sensing scheduling in energy harvesting sensor networks," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2014, pp. 4077–4082.

[8] H. Kim and K. G. Shin, "Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks," *IEEE Trans. Mobile Comput.*, vol. 7, no. 5, pp. 533–545, May 2008.

[9] G. A. Shah and O. B. Akan, "Cognitive adaptive medium access control in cognitive radio sensor networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 2, pp. 757–767, Feb. 2015.

[10] R. Deng, J. Chen, C. Yuen, P. Cheng, and Y. Sun, "Energy-efficient cooperative spectrum sensing by optimal scheduling in sensor-aided cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 61, no. 2, pp. 716–725, Feb. 2012.

[11] M. Najimi, A. Ebrahimzadeh, S. M. H. Andargoli, and A. Fallahi, "Lifetime maximization in cognitive sensor networks based on the node selection," *IEEE Sensors J.*, vol. 14, no. 7, pp. 2376–2383, Jul. 2014.

[12] N. Zhang, N. Cheng, N. Lu, H. Zhou, J. W. Mark, and X. Shen, "Risk-aware cooperative spectrum access for multi-channel cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 3, pp. 516–527, Mar. 2014.

[13] A. Ebrahimzadeh, M. Najimi, S. M. H. Andargoli, and A. Fallahi, "Sensor selection and optimal energy detection threshold for efficient cooperative spectrum sensing," *IEEE Trans. Veh. Technol.*, vol. 64, no. 4, pp. 1565–1577, Apr. 2015.

[14] S. Eryigit, S. Bayhan, and T. Tugcu, "Energy-efficient multichannel cooperative sensing scheduling with heterogeneous channel conditions for cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 6, pp. 2690–2699, Jul. 2013.

[15] S. Bayhan and F. Alagoz, "Scheduling in centralized cognitive radio networks for energy efficiency," *IEEE Trans. Veh. Technol.*, vol. 62, no. 2, pp. 582–595, Feb. 2013.

[16] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008.

[17] J. Yang, X. Wu, and J. Wu, "Optimal scheduling of collaborative sensing in energy harvesting sensor networks," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 3, pp. 512–523, Mar. 2015.

[18] S. M. Mishra, A. Sahai, and R. W. Brodersen, "Cooperative sensing among cognitive radios," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Istanbul, Turkey, Jun. 2006, pp. 1658–1663.

[19] E. G. Larsson and M. Skoglund, "Cognitive radio in a frequency planned environment: Can it Work?" in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Nov. 2007, pp. 3548–3552.

[20] S. Atapattu, C. Tellambura, and H. Jiang, *Energy Detection for Spectrum Sensing in Cognitive Radio* (Springer Briefs in Computer Science). New York, NY, USA: Springer-Verlag, 2014.

[21] R. Y. Rubinstein, "The cross-entropy method for combinatorial and continuous optimization," *Methodol. Comput. Appl. Probab.*, vol. 1, no. 2, pp. 127–190, Sep. 1999.

[22] P.-T. de Boer, D. P. Kroese, S. Mannor, and R. Y. Rubinstein, "A tutorial on the cross-entropy method," *Ann. Oper. Res.*, vol. 134, no. 1, pp. 19–67, 2005.

[23] J. Zhu, Y. Song, D. Jiang, and H. Song, "Multi-armed bandit channel access scheme with cognitive radio technology in wireless sensor networks for the Internet of Things," *IEEE Access*, vol. 4, pp. 4609–4617, 2017.

[24] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347–2376, 4th Quart., 2015.

[25] G. Alippi and C. Galperti, "An adaptive system for optimal solar energy harvesting in wireless sensor network nodes," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 55, no. 6, pp. 1742–1750, Jul. 2008.

[26] F. Sangare, Y. Xiao, D. Niyato, and Z. Han, "Mobile charging in wireless-powered sensor networks: Optimal scheduling and experimental implementation," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7400–7410, Aug. 2017.

[27] A. Hentati, E. Driouch, J. F. Frigon, and W. Ajib, "Fair and low complexity node selection in energy harvesting wireless sensor networks," *IEEE Syst. J.*, to be published.

[28] J. Ren, J. Hu, D. Zhang, H. Guo, Y. Zhang, and X. Shen, "RF energy harvesting and transfer in cognitive radio sensor networks: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 56, no. 1, pp. 104–110, Jan. 2018.

[29] F. Li, H. Jiang, R. Fan, and P. Tan, "Optimal cooperative strategy in energy harvesting cognitive radio networks," in *Proc. IEEE Veh. Technol. Conf.*, Sep. 2017, pp. 1–6.

[30] S. Aslam, W. Ejaz, and M. Ibnkahla, "Energy and spectral efficient cognitive radio sensor networks for Internet of Things," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 3220–3233, Aug. 2018.

[31] C. Majumdar, D. Lee, A. A. Patel, S. N. Merchant, and U. B. Desai, "Packet size optimization for cognitive radio sensor networks aided Internet of Things," *IEEE Access*, vol. 5, pp. 6325–6344, 2017.

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