Energy Efficiency Maximization for Green Cognitive Internet of Things with Energy Harvesting

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Abstract. In this paper, a green cognitive Internet of Things (CIoT) has been proposed to collect the radio frequency (RF) energy of primary user (PU) by using energy harvesting. The CIoT nodes are divided into two independent groups to perform spectrum sensing and energy harvesting simultaneously in the sensing slot. The energy efficiency of the CIoT is maximized by through jointly optimizing sensing time, number of sensing nodes and transmission power. The suboptimal solution to the optimization problem is achieved using a joint optimization algorithm based on alternating direction optimization. Simulation results have indicated that the optimal solution is existed and the green CIoT outperforms the traditional scheme.

Keywords: CIoT · Energy efficiency · Energy harvesting · Joint optimization

1 Introduction

Cognitive radio (CR) has been proposed to improve spectrum utilization by accessing the idle spectrum of a primary user (PU), providing that the normal communications of the PU cannot be disturbed [1]. In order to avoid causing any interference to the PU, the CR has to perform spectrum sensing before using an idle channel and access this channel only when detecting the absence of the PU [2]. Cooperative spectrum sensing exploiting sensing diversity gain is proposed as a high-performance spectrum sensing method, which allows multiple

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nodes to sense the PU collaboratively and gets a final decision by combining local sensing results of all the nodes with some fusion rules [3,4]. A sensing-throughput tradeoff scheme has been proposed to maximize the throughput of the CR by selecting an optimal sensing time [5].

Internet of things (IoT) has gotten more and more attentions with the development of social and economy, which connects everything through the internet and provides better quality of service (QoS) to users [6]. However, the IoT can only use some unlicensed spectrum that is competitively used by many communication equipments, such as WiFi, Bluetooth and WiMax etc. Thus, the inadequate spectrum resources have greatly limited the development of the IoT [7,8]. IoT combining with CR, namely cognitive IoT (CIoT), has been proposed to improve spectrum utilization of a IoT through using idle licensed spectrum. However, compared with the traditional IoTs, CIoT may consume more energy due to spectrum sensing [9]. Hence, it is an important to realize green CIoT.

Wireless energy harvesting has been investigated to realize green communications by collecting the radio frequency (RF) energy of ambient signal sources, which can convert RF energy to direct current (DC) voltage by deploying a rectifying circuit [10,11]. To guarantee enough transmission power, energy harvesting has been used in CR to collect the RF energy of a PU's signal following spectrum sensing [12]. In the previous literatures, resource optimizations are presented to maximize the transmission performance of the IoT, however, the energy efficiency optimization is not considered. In this paper, a green CIoT is proposed to decrease energy consumption using energy harvesting. The contributions of the paper are listed as follows

- A green CIoT is proposed to collect the RF energy of the PU's signal and the noise for compensating sensing energy consumption. The frame is divided into sensing slot and transmission slot, and the CIoT nodes are divided into two independent groups to perform spectrum sensing and energy harvesting simultaneously in the sensing slot.
- The maximization of energy efficiency by jointly optimizing sensing time, number of sensing nodes and transmission power is formulated as a multi-parameter non-convex optimization problem that is hard to be solved directly. A joint optimization algorithm has been proposed to achieve the suboptimal solution to the optimization problem.

2 System Model

Periodical spectrum sensing and transmission has been proposed to improve the spectrum efficiency of the CIoT, while avoiding producing any interference to the PU [13]. The frame structure of the CIoT is divided into sensing slot and transmission slot, and the transmission happens only when the PU has been detected in the sensing slot, as shown in Fig. 1.

However, compared with the traditional IoTs, the CIoT may consume more energy due to the energy consumption in spectrum sensing. Hence, a green CIoT is proposed to harvest the RF energy of the PU's signal to supplement energy consumption. In the sensing slot of the energy-efficient CIoT, a group of CIoT nodes detect the presence of the PU by cooperative spectrum sensing, while the other group of nodes collect the RF energy of the PU's signal using energy harvesting simultaneously, as shown in Fig. 2.

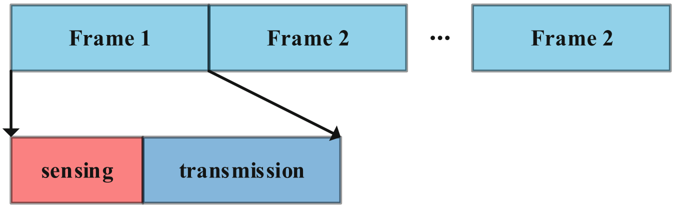

Fig. 1. Frame structure of CIoT.

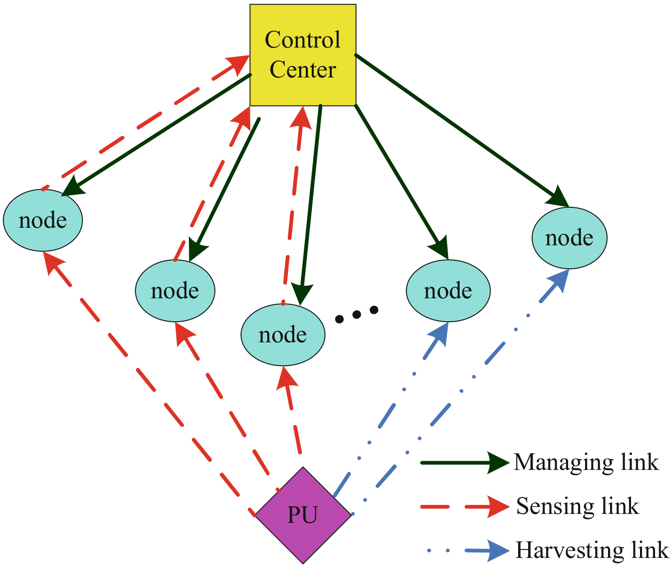

Fig. 2. Green CIoT structure.

We suppose that there are N nodes and one control center in the CIoT and K nodes are selected to perform cooperative spectrum sensing. In cooperative spectrum sensing, each node first senses the PU to get local detection information, and then all the detection information of K nodes are sent to the control center for combination [14]. The final decision is made at the control center by comparing the combined detection information to a threshold. The presence of the PU is decided if the combined detection value is above the preset threshold, otherwise, the absence of the PU is determined. False alarm probability and detection probability of cooperative spectrum sensing are respectively given as follows

$$P_d = Q\left(\left(\frac{\lambda}{\sigma_n^2} - \gamma - 1\right)\sqrt{\frac{Kt_s f_s}{(1+\gamma)^2}}\right) \tag{1}$$

$$P_f = Q\left(\left(\frac{\lambda}{\sigma_n^2} - 1\right)\sqrt{Kt_s f_s}\right) \tag{2}$$

where λ is detection threshold, σ_n^2 is noise power, γ is average PU's signal to noise ratio (PSNR), t_s is sensing time and f_s is sampling frequency.

P_f indicates the spectrum utilization of the CIoT, which should be decreased to improve the spectrum access probability of the CIoT; while P_d reflects the interference to the PU, whose should be increased to decrease the interference probability of the CIoT. As the primary task of the CIoT is to avoid causing harmful interference to the PU, the detection probability is often constrained as $P_d \geq P_d^{min}$, where P_d^{min} is the minimal detection probability satisfying the interference tolerance of the PU. Then the constraint of P_f is given by

$$P_f \geq Q\left(Q^{-1}(P_d^{min})(\gamma + 1) + \gamma\sqrt{Kt_s f_s}\right) \tag{3}$$

The RF energy of wireless signals can be collected to convert to DC energy by a wireless system deploying an energy harvester with a rectifying circuit as the core device. The harvested energy is then stored in a rechargeable battery of the wireless system. In the CIoT, the remaining $N - K$ nodes are selected to harvest the RF energy of the PU's signal and the noise in the channel in the sensing slot. The harvested power of each node can be given by

$$p_h = u(1+\gamma)\sigma_n^2 \tag{4}$$

where u is energy-harvesting efficiency.

Assume that each sensing node reports its detection information to the control center in an independent time slot in case of transmission conflicts. The reporting time can be seen as cooperative sensing overhead, t_c, which is described as $t_c = K\tau$, where τ is the slot length. Thus, the total sensing slot length $T_s = t_s + t_c$. Supposing the frame time is T, the transmission time $T_d = T - T_s$. The CIoT can transmit data effectively only when the absence of the PU has been detected accurately in the probability of $(1 - P_f)P_0$ where P_0 is average idle probability of the PU. The average total throughput of the CIoT is given by

$$R = (T - t_s - K\tau)(1 - P_f)P_0 C \tag{5}$$

where C is transmission rate defined as follows

$$C = \sum_{n=1}^{N} \log\left(1 + \frac{p_i h_i^2}{\sigma_n^2}\right) \tag{6}$$

where p_i and h_i is transmission power and channel gain of node i, respectively.

The CIoT may consume energy during spectrum sensing and data transmission but save energy by energy harvesting. The total consumed sensing energy is given by $E_s = Kp_sT_s$ where p_s is average sensing power in the sensing slot, the total consumed transmission energy is obtained by $E_d = p_tT_d$ where p_t is total power of N nodes, and the total harvested energy is given by $E_h = (N-K)p_hT_s$. Hence, the total consumed energy $E_c = E_s + E_d - E_h$. The energy efficiency of the CIoT, which is related with the parameters t_s, K and $\{p_i\}$, can be defined as follows

$$\eta\left(t_s, K, \{p_i\}\right) = \frac{R}{E_c} = \frac{(T - t_s - K\tau)(1 - P_f)P_0 \sum_{i=1}^{N} \log\left(1 + \frac{p_i h_i^2}{\sigma_n^2}\right)}{Kp_sT_s + p_tT_d - (N-K)p_hT_s} \tag{7}$$

3 Model Optimization

In this paper, we try to maximize the energy efficiency of the CIoT by jointly optimizing sensing time, number of sensing nodes and transmission power, subject to the constraints of detection probability and transmission rate. The optimization problem is listed as follows

$$\max_{t_s, K, \{p_i\}} \quad \eta\left(t_s, K, \{p_i\}\right) \tag{8a}$$

$$\text{s.t.} \quad P_d \geq P_d^{min} \tag{8b}$$

$$C \geq C^{min} \tag{8c}$$

$$t_s + K\tau \leq T \tag{8d}$$

$$p_i \geq 0, i = 1, 2, ..., N \tag{8e}$$

$$1 \leq K \leq N, K \in Z \tag{8f}$$

where C^{min} is the minimal transmission rate. This is a multi-parameter non-convex optimization problem that is hard to be solved directly. In this paper, a suboptimal solving algorithm is proposed, which divides the optimization problem into two sub-optimization problems.

3.1 Power Optimization

From (7), η can be maximized with the minimal p_t, hence, an optimization problem to minimize p_t under the constraint of C is first given as follows

$$\min_{\{p_i\}} \quad p_t = \sum_{i=1}^{N} p_i \tag{9a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} \log\left(1 + \frac{p_i h_i^2}{\sigma_n^2}\right) \geq C^{min} \tag{9b}$$

$$p_i \geq 0, i = 1, 2, ..., N \tag{9c}$$

which can be solved by Lagrange optimization. The Lagrange function is given as follows

$$L\left(\lambda, \{p_i\}\right) = \sum_{i=1}^{N} p_i - \lambda\left(\sum_{n=1}^{N} \log\left(1 + \frac{p_i h_i^2}{\sigma_n^2}\right) - C^{min}\right) \tag{10}$$

where $\lambda > 0$ is Lagrange multiplier. The optimal power value p_i^* is achieved by letting $\frac{\partial L(\lambda, \{p_i\})}{p_i} = 0$ for $i = 1, 2, ..., N$. Noting that $p_i \geq 0$, p_i^* is calculated by

$$p_i^* = \left(\lambda - \frac{\sigma_n^2}{h_i^2}\right)^+ \tag{11}$$

where $(x)^+$ denotes the maximal value between x and 0.

3.2 Joint Optimization

After the optimal $\{p_i\}$ is achieved, t_s and K are jointly optimized. The optimization problem is formulated as follows

$$\max_{t_s, K} \quad \eta\left(t_s, K\right) = \frac{(T - t_s - K\tau)(1 - P_f)P_0 C^{min}}{\left(Kp_s - (N - K)p_h\right)\left(t_s + K\tau\right) + p_t^*(T - t_s - K\tau)} \tag{12a}$$

$$\text{s.t.} \quad P_d \geq P_d^{min} \tag{12b}$$

$$t_s + K\tau \leq T \tag{12c}$$

$$1 \leq K \leq N, K \in Z \tag{12d}$$

where $p_t^* = \sum_{i=1}^{N} p_i^*$. From (12), η improves with the decrease of P_f, hence, the maximal value of η can be achieved only when η equals its lower bound as shown in (3). The objective function η is rewritten as follows

$$\eta\left(t_s, K\right) = \frac{P_0 C^{min}(T - t_s - K\tau)\left(1 - Q\left(Q^{-1}(P_d^{min})(\gamma + 1) + \gamma\sqrt{Kt_s f_s}\right)\right)}{\left(Kp_s - (N - K)p_h\right)\left(t_s + K\tau\right) + p_t^*(T - t_s - K\tau)} \tag{13}$$

Firstly fixing K, we optimize t_s. Then let $\eta(t_s) = \frac{f_a(t_s)}{f_b(t_s)}$, where $f_a(t_s)$ and $f_b(t_s)$ are respectively given by

$$f_a(t_s) = P_0 C^{min}(T - t_s - K\tau)\left(1 - Q\left(Q^{-1}(P_d^{min})(\gamma+1) + \gamma\sqrt{K t_s f_s}\right)\right) \quad (14)$$

$$f_b(t_s) = (Kp_s - (N-K)p_h)(t_s + K\tau) + p_t^*(T - t_s - K\tau) \quad (15)$$

It has been proven that $f_a(t_s)$ is a convex function, meanwhile, $\eta_b(t_s)$ is a linear function. Hence, (12) can be solved by Dinkelbach's optimization that can solve convex-linear fractional optimization by an iterative procedure. An equivalent optimization function $F(\eta_l)$ is defined as follows

$$F(\eta^{(l)}) = f_a(t_s^{(l)}) - \eta^{(l)} f_b(t_s^{(l)}) \quad (16)$$

where l is iteration index. In each iteration, we try to maximize $F(\eta^{(l)})$. The optimal $\eta^{(l)} = \frac{f_a(t_s^{(l)})}{f_b(t_s^{(l)})}$ can be achieved when $F(\eta^{(l)})$ is convergent. The sensing time optimization algorithm is shown as Algorithm 1.

Algorithm 1. Sensing time optimization.

```
Input: $\eta^{(l)} = 0$ where $l = 1$, and the convergence accuracy $\delta$;
1: while $F(\eta^{(l)}) > \delta$ do
2:     find the optimal solution to the optimization problem $t_s^{(l)} = arg\,max\left(f_a(t_s^{(l)}) - \eta^{(l)} f_b(t_s^{(l)})\right)$ using interior-point method;
3:     set $\eta^{(l+1)} = \frac{f_a(t_s^{(l)})}{f_b(t_s^{(l)})}$ and $l = l + 1$;
4: end while
Output: the optimal solution $t_s^* = t_s^{(l)}$.
```

Then with the optimal t_s^*, we continue to optimize K. Since K is an integer within $[0, N]$, it is not computational complexity to search optimal K^* using enumeration method, as follows

$$K^* = \arg\max_{1 \le K \le N} \eta\left(K | t_s = t_s^*\right) \quad (17)$$

Then we use ADO to achieve the joint optimal solution [15], through optimizing t_s and K alternatively until both of them are convergent. The joint optimization algorithm is described as Algorithm 2.

4 Simulations and Discussions

In the simulations, the frame time $T = 10\,\text{ms}$, the sampling frequency $f_s = 10\,\text{KHz}$, the number of nodes $N = 20$, the sensing power $p_s = 3\,\text{mW}$, the noise

Algorithm 2. Joint optimization algorithm.

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Input: $t_s^{(l)} = 0$ and $K^{(l)} = 1$;
while $t_s$ and $K$ are not convergent or reaching the maximal iterations do
    fixing $K = K^{(l)}$, achieve optimal $t_s^*$ using the Algorithm 1;
    set $t_s^{(l+1)} = t_s^*$;
    fixing $t_s = t_s^{(l+1)}$, achieve optimal $K^*$ using enumeration method;
    set $K^{(l+1)} = K^*$ and $l = l + 1$;
end while
Output: the joint optimal solution $t_s^* = t_s^{(l)}$ and $K^* = K^{(l)}$.
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power $\sigma_n^2 = 0.1\text{mW}$, the energy-harvesting efficiency $u = 50\%$, the idle probability $P_0 = 0.5$, the minimal transmission rate $C^{min} = 100\,\text{Kbps}$, and the average channel gain is $-5\,\text{dB}$.

Figure 3 shows energy efficiency η changing with sensing time t_s and number of sensing nodes K. It is seen that there is an optimal set of t_s and K that maximizes η. η first improves with the increase of t_s because of the improved spectrum access probability, and then decreases due to the increased energy consumption. Moreover, η has the similar trend with the increase of K, which first improves due to the increase of sensing performance but then decreases because of the increase of sensing overhead.

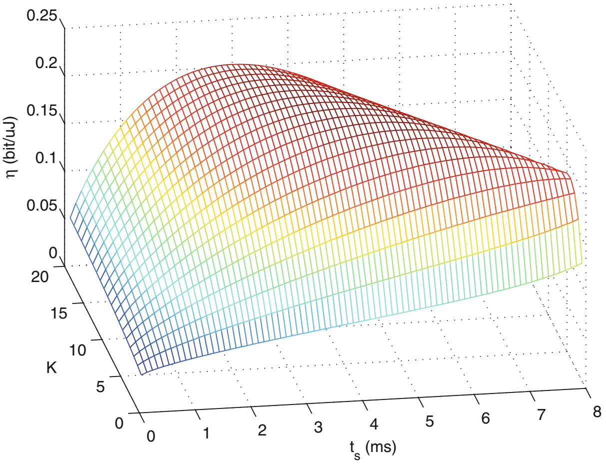

Fig. 3. Energy efficiency changing with sensing time and number of sensing nodes.

Figure 4 indicates throughput R changing with consumed energy E_c. It is seen that R first improves and then decreases as E_c increases, because the increase of E_c may improve the transmission performance but also increase the sensing overhead. Thus, there is tradeoff between transmission performance and

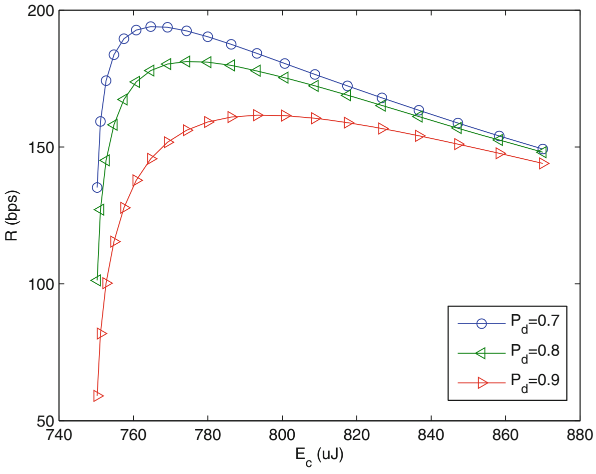

Fig. 4. Throughput changing with consumed energy.

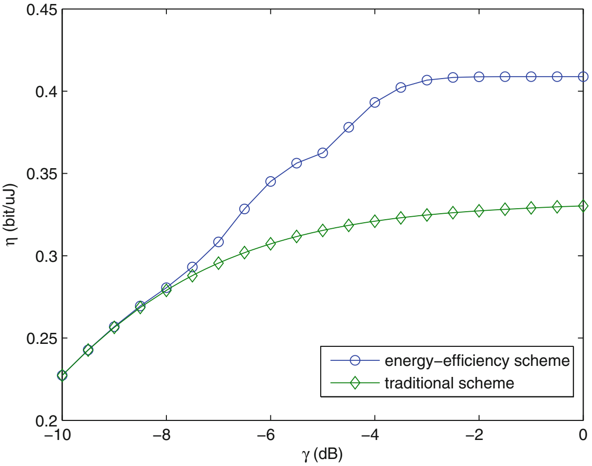

Fig. 5. Energy efficiency comparison.

energy consumption. Figure 5 compares energy efficiency of the proposed energy-efficient scheme and the traditional scheme. It shows that the proposed scheme can achieve larger energy efficiency as the PSNR increases.

5 Conclusions

In this paper, a green CIoT is proposed to harvest RF energy of the PU's signal to compensate sensing energy consumption. The energy efficiency of the green CIoT is maximized by jointly optimizing sensing time, number of sensing nodes and transmission power. From the simulations, there is an optimal set of sensing time and number of sensing nodes that maximizes the energy efficiency, and the green CIoT can achieve larger energy efficiency compared with the traditional CIoT.

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