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Throughput Optimization in Energy Harvesting based Cognitive IoT with Cooperative Sensing

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***Abstract*—In this paper, we study the throughput optimization problem in energy harvesting based cognitive Internet of Things (IoT), under cooperative spectrum sensing mode. Considering the user diversity in energy harvesting efficiency, spectrum sensing performance and data quality-of-service requirement, we optimize the harvesting-sensing-transmission tradeoff. To achieve this, we formulate it as a network-level throughput optimization problem by jointly optimizing time splitting and sensor selection. With the proposed throughput-based greedy algorithm, we first fix the sensor selection variable, and then transform the problem into an equivalent convex optimization problem. Simulation results show that our proposed scheme has great advantages in terms of secondary network throughput.**

***Index Terms*—Cooperative Sensing, Cognitive IoT, Energy Harvesting**

I. Introduction

Internet of Things (IoT) is a recent technology connecting massive devices to provide ubiquitous communication experience. The boosting growth of data traffic among connected devices in IoT heavily relies on the radio spectrum resource. Cognitive radio is deemed as a promising way in IoT to accommodate the scarcity of spectrum resource, where IoT devices perform as secondary users (SUs) to obtain more transmission opportunity [1]–[3]. Besides, energy resource is also important especially for outdoor IoT devices, since the power line may not be available and frequent replacement of batteries may introduce significant operational expenditure. Harvesting energy from the renewable sources (e.g., wind, solar, ambient radio power and vibration) gives a solution to eliminate the energy issues in IoT [4].

Therefore, energy harvesting based cognitive radio network has been widely investigated [5], [6]. Liang et al. in [7] investigate the tradeoff issue between spectrum sensing and data transmission in cognitive radio networks. Based on this work, Yin et al. in [8] discuss harvesting-sensing-transmission tradeoff under both data-fusion and decision-fusion strategies. Bae et al. in [9] discuss the optimal sensing strategy to maximize the SU throughput under the energy causality constraint. Li et al. in [10] study the joint optimization of sensing energy, transmission energy and sensing interval, under partially observable Markov decision process.

However, a premise behind these existing works is non-cooperative sensing mode, where SUs sense individually. The sensing performance such as detection probability is often compromised with shadowing, fading and receiver uncertainty. To overcome this, cooperative sensing method, combining decisions from spatially distributed SUs, is studied to improve sensing efficiency by exploring spatial diversity in cognitive radio networks [11].

With cooperative sensing, the energy-harvesting based cognitive radio network faces more challenges. First, under cooperative sensing, multiple SUs sense together to achieve a combined decision. Thus, SUs with limited harvesting capability but large transmission demands, could prevent from sensing, and directly use the final decision resulted from other sensing SUs. This provides more flexibility in resource allocation. It helps such energy-constrained SUs to save sensing energy for more transmissions, as well as helps them to gain more time for energy harvesting. Second, the sensing strategy including sensor selection, sensing time allocation and decision threshold setting, directly impacts on the final sensing performance. This further influences the throughput of both primary users (PUs) and SUs. Besides, the time and energy resource remaining for SU transmission is also impacted by sensing strategy. Hence, the harvesting-sensing-transmission tradeoff problem becomes further complicated under the cooperative spectrum sensing mode.

To this end, in this paper we study the throughput optimization in energy harvesting based cognitive IoT, under cooperative spectrum sensing mode. Considering the user diversity of secondary IoT device in harvesting efficiency, sensing performance and quality-of-service (QoS) requirement, we propose a novel resource allocation scheme to maximize the network-level throughput in secondary IoT networks. We formulate the network-level throughput optimization problem in secondary IoT, by jointly optimizing time splitting and sensor selection. Then we propose a throughput based greedy algorithm to solve it. Simulations show that the proposed scheme outperforms other schemes in terms of secondary network throughput. Our main contributions are as follows:

- Based on the time splitting, PU protection, energy causality and QoS requirement constraints, we jointly formulate the throughput optimization problem for secondary IoT network from two aspects: 1) time splitting to determine the time duration for energy harvesting, spectrum sensing and transmission periods. 2) sensor selection scheme to choose SUs to perform cooperative spectrum sensing;
- To solve it, we propose a throughput-based greedy algorithm. In this algorithm, we first fix the binary sensor selection variables. Then, based on the feature of log-concave function, we transform the sub-problem into a

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convex optimization problem and easily solve it through traditional optimization means;

- Simulations show that the proposed scheme has great advantages in terms of secondary network throughput.

II. System Model

We consider an energy-harvesting based cognitive IoT with one PU transmitter, one fusion center (FC), and N SUs (We use secondary user and secondary IoT device interchangeably in this paper). Note that the FC also plays a role as secondary access point (SAP) to receive data traffic from SUs. Denoting the idle probability of PU as Pr_0. Time is discretized into frames. We assume channel fading are independent and identically distributed (i.i.d.) across frames, and independent across different SUs. Channel gains change over time, but remain constant within each frame. The channel gain between FC and SU_i is denoted as g_i.

A. Time Splitting Structure

As illustrated in Fig. 1, frame with length T is split into energy harvesting, spectrum sensing, and data transmission periods. These three periods are non-overlapping due to the energy half-duplex constraint which prevents battery from charging and discharging simultaneously [6].

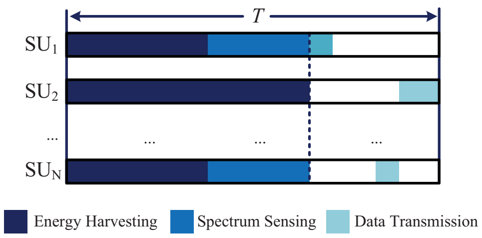

Fig. 1. Time Splitting in a Frame

In each frame, SUs first harvest energy from ambient within duration τ_H. We assume infinite battery capacity and denote the harvesting efficiency of SU_i as P_{Hi}. After energy harvesting, SUs perform spectrum sensing within duration τ_S. If SU_i is selected to sense, we have $\delta_i = 1$, otherwise $\delta_i = 0$. If SU_i does not participate in sensing, it keeps harvesting during sensing period. Power consumed for sensing of SU_i is denoted by P_{Si}.

After spectrum sensing, once PU is declared to be inactive, SUs access idle spectrum to transmit to SAP. The transmission time allocated for SU_i is τ_{Ti}. To avoid collision at SAP and mitigate harmful interference to PU, multiple SUs may not transmit simultaneously, i.e., τ_{Ti} of SUs is also non-overlapping. The transmission power of SU_i is P_{Ti}. Considering the QoS diversity of secondary applications, for SU_i, we denote its minimal achievable rate requirement as $\bar{R}_i$, which should be satisfied during data transmission. Therefore, under the normalized channel bandwidth and additive Gaussian noise with noise power σ_u^2, the transmission rate of SU_i in a frame can be caculated as

$$R_i(\tau_{Ti}) = \frac{\tau_{Ti}}{T}\log(1 + \frac{|g_i|^2 P_{Ti}}{\sigma_u^2}), \tag{1}$$

B. Cooperative Spectrum Sensing

The energy detection method is adopted to spectrum sensing in this paper, since no prior information of detected signal is required. We consider complex PSK modulated signal and circularly symmetric complex Gaussian noise for primary signal. For the cooperative sensing case, we utilize the widely used OR-rule at FC. That is, PU is claimed to be busy when at least one sensing SU claims the presence of PU. Hence, from [7], to measure the sensing performance, the overall false alarm probability Pr_f and detection probability Pr_d under cooperative sensing mode can be expressed as

$$Pr_f = 1 - \prod_{i=1}^{N}(1 - \delta_i Pr_{fi}). \tag{2}$$

$$Pr_d = 1 - \prod_{i=1}^{N}(1 - \delta_i Pr_{di}). \tag{3}$$

where Pr_{fi} and Pr_{di} are the individual false alarm probability and individual detection probability of SU_i, respectively.

Generally specking, to protect PUs from collision, the overall detection probability Pr_d is always required to be larger than a given threshold $\overline{Pr_d}$. Once δ_i is fixed (i.e., the sensor selection scheme is fixed), based on (3), the given threshold $\overline{Pr_d}$ could further derive a threshold $\overline{Pr_{di}}$ for individual SU by assuming that $\overline{Pr_{di}}$ is the same for all SUs (i.e., $\overline{Pr_{d1}} = \ldots = \overline{Pr_{di}} = \ldots = \overline{Pr_{dN}}$).

Moreover, given $\overline{Pr_{di}}$, the false alarm probability of SU_i could be calculated as [7]

$$Pr_{fi}(\tau_S) = Q(\sqrt{2\gamma_i + 1}Q^{-1}(\overline{Pr_{di}}) + \sqrt{\tau_S f}\gamma_i), \tag{4}$$

where γ_i is the received signal-to-noise ratio (SNR) of primary signal detected by SU_i. f is the sampling frequency. $Q(\cdot)$ refers to the complementary cumulative distribution function of a standard Gaussian probability density.

III. Problem Formulation

A. Time Splitting Constraint

Based on the analysis above, the energy harvesting, spectrum sensing and data transmission periods are non-overlapping. Hence, their summation should be less than the frame length. That is,

$$\tau_H + \tau_S + \sum_{i=1}^{N}\tau_{Ti} \le T. \tag{5}$$

B. Energy Causality Constraint

For each SU_i, the total energy harvested during a frame is $\tau_H P_{Hi} + \tau_S P_{Hi}(1 - \delta_i)$, which means the energy harvested during the harvesting period τ_H, and during the sensing period τ_S if the SU does not join in spectrum sensing.

The energy consumed during a frame is $\tau_{Ti}P_{Ti} + \tau_S P_{Si}\delta_i$, which means the energy consumed for data transmission, and for sensing if the SU performs spectrum sensing.

Obviously, the consumed energy should be no larger than the energy stored. Thus we have the following energy causality constraint as

$$\tau_{Ti}P_{Ti} + \tau_S P_{Si}\delta_i \le E_i + \tau_H P_{Hi} + \tau_S P_{Hi}(1-\delta_i), \quad (6)$$

where E_i is the residual energy in battery at the beginning of each frame. Since E_i is a constant and will not affects the solution, we assume $E_i = 0$ in this paper.

C. PU Protection Constraint

To protect PUs from interference, the overall detection probability under cooperative sensing should be larger than a given threshold $\overline{Pr_d}$, that is,

$$1 - \prod_{i=1}^{N}(1 - \delta_i \overline{Pr_{di}}) \ge \overline{Pr_d}. \quad (7)$$

D. QoS Requirement Constraint

Based on equations (1), for each SU_i, the achievable transmission rate with transmission duration τ_{Ti} is $Pr_0(1 - Pr_f(\tau_S))R_i(\tau_{Ti})$.

To guarantee QoS requirement for each SU, the achievable rate should be no less than its individual rate requirement $\bar{R}_i$, i.e.,

$$Pr_0(1 - Pr_f(\tau_S))R_i(\tau_{Ti}) \ge \bar{R}_i, \quad (8)$$

where $Pr_f(\tau_S)$ can be calculated based on (2) and (4).

E. Network-Level Throughput Maximization

The objective function is to maximize the overall throughput of secondary IoT. Thus, we have

$$\max_{\tau_H,\tau_S,\tau_{Ti},\delta_i} Pr_0(1 - Pr_f(\tau_S))\sum_{i=1}^{N} R_i(\tau_{Ti}). \quad (9)$$

F. Overall Optimization Problem

Based on the analysis above, to maximize the summation throughput in cognitive IoT, we jointly formulate the energy harvesting, spectrum sensing and data transmission problem with cooperative sensing mode as follows

$$\max_{\tau_H,\tau_S,\tau_{Ti},\delta_i} Pr_0(1 - Pr_f(\tau_S))\sum_{i=1}^{N} R_i(\tau_{Ti}) \quad (10)$$

$$\text{s. t. } \tau_H + \tau_S + \sum_{i=1}^{N}\tau_{Ti} \le T, \quad (11)$$

$$\tau_{Ti}P_{Ti} + \tau_S P_{Si}\delta_i \le \tau_H P_{Hi} + \tau_S P_{Hi}(1-\delta_i), \forall i, \quad (12)$$

$$1 - \prod_{i=1}^{N}(1 - \delta_i \overline{Pr_{di}}) \ge \overline{Pr_d} \quad (13)$$

$$Pr_0(1 - Pr_f(\tau_S))R_i(\tau_{Ti}) \ge \bar{R}_i, \forall i, \quad (14)$$

$$\delta_i \in \{0,1\}, \forall i. \quad (15)$$

IV. Throughput based Greedy Algorithm

Because binary variables δ_i are involved, it is obvious that the problem in (10)-(15) is a mixed-integer and nonlinear optimization problem, which is difficult to solve through existing standard optimization methods.

To this end, in this section, we propose a throughput-based greedy algorithm to sub-optimally solve this problem. Here is the basic idea behind this algorithm: We first fix the binary variables δ_i under a sensor selection scheme. Then, for the sub-problem with continuous variables, since it is still non-convex, we transform it into an equivalent convex optimization problem through mathematical transformation methods. In this way, we could use traditional optimization algorithms to easily solve this convex problem.

A. Sub-problem Transformation

Under a specific sensor selection scheme, the integer values of δ_i could be determined. Then, in constraint (7), the individual detection probability threshold $\overline{Pr_{di}}$ can be calculated through a given $\overline{Pr_d}$ and constraint (7) can be satisfied. But for the remaining sub-problem with continuous variables τ_H, τ_S and τ_{Ti}, it is still non-convex since the presence of $Q(\cdot)$ function.

To overcome it, we introduce auxiliary variables $\alpha_i = \sqrt{2\gamma_i + 1}Q^{-1}(\overline{Pr_{di}})$ and $\beta = \sqrt{\tau_S}$. Then equation (4) can be rewritten as

$$Pr_{fi}(\beta) = Q(\alpha_i + \beta\sqrt{f}\gamma_i), \quad (16)$$

Note that α_i, γ_i, and f are constants. β is a variable.

Consequently, we have

$$1 - Pr_{fi}(\beta) = 1 - Q(\alpha_i + \beta\sqrt{f}\gamma_i) = \Phi(\alpha_i + \beta\sqrt{f}\gamma_i), \quad (17)$$

where $\Phi(\cdot)$ refers to the cumulative distribution function of a standard Gaussian probability density. It is proved that the function $\Phi(\cdot)$ is log-concave [12], meaning that $\log\big(\Phi(\cdot)\big)$ is concave.

As a result, $\Phi(\alpha_i + \beta\sqrt{f}\gamma_i)$ is log-concave in terms of variable β. It can be further proved that the product of log-concave functions is also log-concave. Inspired by this feature, for the cooperative false alarm probability $Pr_f(\beta)$ in (2), we can infer that

$$1 - Pr_f(\beta) = \prod_{i \in sense\ set}\Phi(\alpha_i + \beta\sqrt{f}\gamma_i), \quad (18)$$

is also log-concave, where the cooperative sensing set is given by fixing δ_i under a sensor selection scheme. Besides, also from [12], the logarithmic transformation of a concave function is still concave.

On the basis of above analysis, the objective function in (10) can be transformed as follows with the logarithmic function.

$$\log\big(Pr_0\big) + \log\Bigg(\prod_{i \in sense\ set}\Phi(\alpha_i + \beta\sqrt{f}\gamma_i)\Bigg) + \log\Big(\sum_{i=1}^{N}R_i(\tau_{Ti})\Big). \quad (19)$$

For equation (19), the first term is a constant. The second term is concave in terms of β. The last term is concave in terms of

τ_{Ti}. This is because $\sum_{i=1}^{N} R_i(\tau_{Ti})$ is linear and concave, and hence its logarithmic transformation is also concave.

Therefore, the optimization problem in (10)-(15) can be transformed as

$$\max_{\tau_H,\beta,\tau_{Ti}} \Big\{ \log\big(Pr_0\big)+ \\ \log\Big(\prod_{i\in \text{sense set}} \Phi(\alpha_i+\beta\sqrt{f}\gamma_i)\Big)+\log\big(\sum_{i=1}^{N} R_i(\tau_{Ti})\big)\Big\} \tag{20}$$

s. t.

$$\tau_H+\beta^2+\sum_{i=1}^{N}\tau_{Ti}\le T, \tag{21}$$

$$\tau_{Ti}P_{Ti}+(T-\tau_H-\sum_{j=1}^{N}\tau_{Tj})P_{Si}\le \tau_H P_{Hi}, \forall i\in \text{sense set}, \tag{22}$$

$$\tau_{Ti}P_{Ti}\le \tau_H P_{Hi}+(T-\tau_H-\sum_{j=1}^{N}\tau_{Tj})P_{Hi}, \forall i\notin \text{sense set}, \tag{23}$$

$$\log\big(Pr_0\big)+\log(1-Pr_f(\beta))+\log\big(R_i(\tau_{Ti})\big)\ge \log(\bar{R}_i), \forall i. \tag{24}$$

It can be seen that the transformed problem (20)-(24) is a convex optimization problem, and thus can be solved through traditional methods like interior-point method with polynomial-time complexity.

B. Sensor Selection Scheme

We design sensor selection scheme in this section. In order to achieve better sensing performance, an intuitive way is to select sensing SUs with higher received SNR of primary signal. However, considering the harvesting-sensing-transmission tradeoff in the network, we propose a throughput-based greedy algorithm for sensor selection.

In this algorithm, for each SU_k, we first postulate that the SU performs sensing individually under the non-cooperative sensing mode, i.e., $\{\delta_{i=k}=1, \delta_{i\neq k}=0\}$. By substituting the value of δ_i in problem (10)-(15), and transforming it into the equivalent convex problem, we can solve the corresponding problem (20)-(23) when SU_k senses individually. The corresponding optimal throughput result is denoted as Throughput_k. Now we have N optimal throughput results for N SUs. We rank SUs in descending order of Throughput_k. Then we choose SU with higher Throughput_k to join in cooperative sensing set and update the corresponding δ_i. Under cooperative sensing, we solve the corresponding problem (20)-(24) with updated δ_i. We record the optimal throughput for each cooperative sensing combination, so forth until the throughput becomes decreasing.

Note that when solving the problem (20)-(23) under non-cooperative sensing mode, we relax the problem by omitting the QoS requirement constraint (24). The purpose is to unfasten the feasible region to get more feasible SUs.

It is thus clear that the proposed algorithm chooses sensing SU according to its throughput performance. While the throughput is obtained under the optimization problem, where energy harvesting, spectrum sensing, and data transmission are jointly involved. Apparently, the proposed algorithm selects sensors through balancing harvesting-sensing-transmission tradeoff, rather than solely considering the sensing performance. Overall, we detail the throughput-based greedy algorithm in Algorithm 1.

Algorithm 1: Throughput-based Greedy Algorithm

Output: Cooperative Sensing Set.

1. Each SU_k performs sensing independently with non-cooperative sensing mode, i.e., $\delta_k=1$ and $\delta_{i\neq k}=0$;
2. Solve problem (20)-(23) by substituting the value of δ_i. The optimal throughput result is denoted as Throughput_k for each SU_k;
3. Rank SUs in descending order of Throughput_k ;
4. Add the SU with largest Throughput_k into cooperative sensing set and update δ_i;
5. Solve problem (20)-(24) with updated δ_i under cooperative-sensing mode;
6. Calculate and record the optimal throughput results, so forth until the throughput performance decreases.

V. Performance Evaluation

We generate a random cognitive IoT network where one PU, one FC and several SUs are randomly located within an area of $1000m\times 1000m$. To obtain the received SNR of primary signal γ_i for each SU, channel gain is modeled with large-scale path loss and small-scale fading, where large-scale path is composed by path loss and shadow fading. The transmission power of PU is $0.05W$. The noise power is $2\times 10^{-12}W$. Harvesting efficiency P_{Hi} and rate requirement $\bar{R}_i$ are randomly selected from $[0, 0.2W]$ and $[0, 10kbps]$, respectively. Besides, we set frame length $T=1000ms$, sampling frequency $f=1MHz$, and sensing power $P_{Si}=0.005W$ for all SUs. The overall detection probability threshold is $\overline{Pr_d}=0.9$.

Under this topology, we compare the throughput performance under three schemes: the proposed throughput-based greedy (Throughput-Greedy), SNR-based greedy and non-cooperative sensing algorithms. Here the SNR-based greedy algorithm selects multiple SUs to join in sensing set in descending order of γ_i. The Non-Cooperation algorithm chooses the SU with the highest γ_i to perform spectrum sensing individually.

We exam the throughput performance versus the idle probability of PUs in Fig. 2 under 6 and 10 SUs scenarios. The transmission power of SU is $0.03W$. It can be seen that as the idle probability increases, more transmission opportunities obtained for SUs, resulting in the ascending throughput under all the three schemes. The proposed Throughput-Greedy algorithm always outperforms other two algorithms in terms of network-level throughput. Besides, the throughput under 10 SUs scenario is larger. This is because more SUs provides more transmission requirements as well as more sensing opportunities to improve spectrum sensing performance.

In Fig. 3, we set the number of SU is 6 and the idle probability of PU is 0.8. We plot the summation throughput of SUs versus the transmission power of SUs. Under three schemes, with the increasing transmission power, the secondary network throughput increases sharply and then becomes steady. The first increasing trend is quite intuitive due to the Shannon's law. After that, the increasing transmission power consumes more transmission energy and thus requires more energy harvesting time. This in return compresses the time duration for transmission. Thus, the increasing transmission power combined with reducing transmission time leads to a steady throughput change.

This inference also be demonstrated in Fig. 4, which shows the time splitting results for a specific sensing SU under the proposed Throughput-Greedy scheme. It reveals that with the increasing transmission power, the SU spends more time for harvesting and thus remains less time for data transmission.

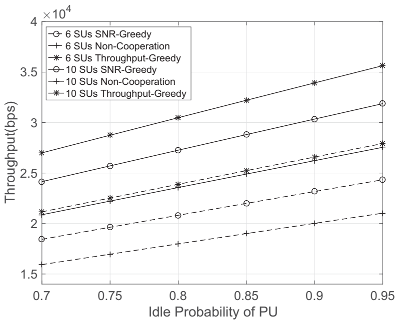

Fig. 2. Secondary Summation Throughput vs. PU Idle Probability

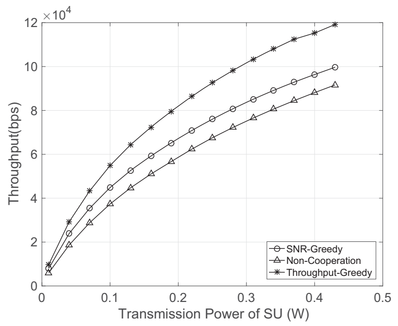

Fig. 3. Secondary Summation Throughput vs. SU Transmission Power

VI. Conclusions

In this paper, we have studied the network-level throughput optimization problem in energy harvesting based cognitive IoT. The harvesting-sensing-transmission tradeoff is investigated under cooperative sensing mode. Time splitting and sensor selection are jointly optimized with the constraints of PU protection, energy causality and QoS requirement. With the proposed throughput-based greedy algorithm, we fix the sensor selection variable first. Then transform the problem into an equivalent convex optimization problem. Through simulations we show that compared with other schemes, the proposed scheme achieves higher secondary network throughput.

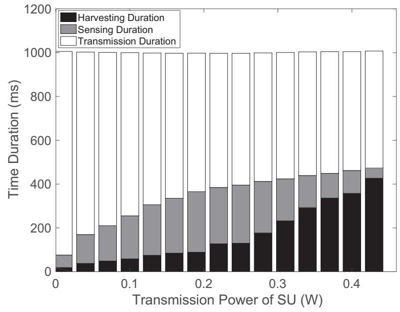

Fig. 4. Time Splitting vs. SU Transmission Power

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