Integrated Cooperative Spectrum Sensing and Access Control for Cognitive Industrial Internet of Things

Xin Liu, *Senior Member, IEEE*, Min Jia, *Senior Member, IEEE*, Mu Zhou, *Senior Member, IEEE*, Bin Wang, , and Tariq S Durrani, *Life Fellow, IEEE*

***Abstract*—Industrial Internet of Things (IIoT) usually utilizes 2.4GHz unlicensed frequency band which is also heavily used by many other communication systems, such as ZigBee, WiFi, Bluetooth, etc. Therefore, the lack of spectrum resources has become a key technical bottleneck to restrict the development of the IIoT. Integrating Cognitive Radio (CR) into IIoT, cognitive IIoT (CIIoT) can cope with the spectrum resource shortage by accessing the frequency bands licensed to primary user (PU). However, spectrum sensing and access control must be performed to avoid bringing severe interference to the PU. In this paper, an integrated cooperative spectrum sensing (CSS) and access control model is proposed to improve the transmission performance of the CIIoT while guaranteeing the CSS's detection probability and controlling the interference to the PU. This model is optimized to maximize the total throughput of the IIoT in each frame by jointly optimizing sensing time, the number of sensing nodes and the transmit power for each node under the constraints of the minimum detection probability, the total power control, the interference control, and the minimum rate for each node. The optimization problem is solved by the joint optimization of spectrum sensing and access control. A simultaneous CSS and access control model is also proposed to increase the communication time by using one time slot to perform CSS and access control simultaneously. The simulation results show that there exist optimal sensing and control parameters to maximize the total throughput of the CIIoT.**

***Index Terms*—Cognitive Industrial Internet of Things; cooperative spectrum sensing; access control; throughput; joint optimization**

This work was supported in part by the National Natural Science Foundation of China under Grants 61771163, U1833102 and U19B2015, in part by the Natural Science Foundation for Outstanding Young Scholars of Heilongjiang Province under Grant YQ2020F001, in part by the Natural Science Foundation of Liaoning Province under Grants 2020-HYLH-13 and 2019-ZD-0014, in part by the Science and Technology on Communication Networks Laboratory under Grants 19641X072 and 18641X028, in part by the advanced research project of civil aerospace technology under Grant No. B0105, in part by the Fundamental Research Funds for the Central Universities under Grant DUT21JC20, and in part by the Engineering Research Center of Mobile Communications of Chinese Ministry of Education. (*Correspondence author: Min Jia*)

X. Liu is with the School of Information and Communication Engineering, Dalian University of Technology, Dalian 116024, China, and also with the State Key Laboratory of Integrated Services Networks, Xidian University, Xian 710071, China (e-mail: liuxinstar1984@dlut.edu.cn).

M. Jia is with the School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin 150080, China (e-mail: jiamin@hit.edu.cn).

M. Zhou is with the Chongqing Key Lab of Mobile Communications Technology, Chongqing University of Posts and Telecommunications, Chongqing 400065, China (e-mail: zhoumu@cqupt.edu.cn).

B. Wang is with the School of Communication Engineering, Xian University of Science and Technology, Xian 710054, China (e-mail:wangbin@mail.xidian.edu.cn).

T. S. Durrani is with the Department of Electronic and Electrical Engineering, University of Strathclyde, Glasgow G1 1XQ, U.K. (e-mail: t.durrani@strath.ac.uk).

I. INTRODUCTION

INDUSTRIAL Internet of Things (IIoT), as the application of IoT technologies in industry, applies intelligent terminals with sensing and interaction abilities, ubiquitous technologies and intelligent analysis to all aspects of industrial production process, so as to greatly improve the manufacturing efficiency [1], [2]. The IIoT usually utilizes 2.4GHz unlicensed frequency band for communications. That frequency band is also adopted by other communication systems, such as ZigBee, WiFi, Bluetooth, etc., and thus becomes very crowded [3]. With the rapid expansion of the industry production scale, the lack of spectrum resources has become a key technical bottleneck to restrict the development of the IIoT [4]. Recently, Cognitive Radio (CR) has been proposed to increase spectrum access opportunities by making full use of unused idle spectrum, where primary user (PU) is not present temporarily. However, the CR system has to control its spectrum access to avoid bringing severe interference to the PU [5]–[7]. Integrating CR into IIoT, Cognitive IIoT (CIIoT) can solve the problem of spectrum resource shortage effectively by accessing the idle frequency bands licensed to the PUs [8], [9].

In the CIIoT, it is important to perform spectrum sensing to find idle channels and control spectrum access to avoid interfering with the PU. However, the traditional spectrum sensing and spectrum access control are independently studied. Energy detection (ED) as an effective spectrum sensing method has been widely used for CR to make a quick decision on the licensed channel state without needing any PU's signal information [10]. However, the ED can't detect weak signal in fading channel correctly. Cooperative spectrum sensing (CSS) can improve detection performance in fading channel by the collaborative sensing and decision of multiple users. In CSS, each user first senses the PU independently by ED and then sends its sensing result to a fusion center. The fusion center will make a global decision on the channel state by combining all the receiving sensing results [11], [12]. False alarm probability and detection probability are two important indicators of spectrum sensing performance. Low false alarm probability will improve the spectrum access efficiency of the CIIoT, while high detection probability will reduce the interference to the PU [13].

This is a peer reviewed, accepted author manuscript of the following research article: Liu, X., Jia, M., Zhou, M., Wang, B., & Durrani, T. S. (2023). Integrated cooperative spectrum sensing and access control for cognitive Industrial Internet of Things. IEEE Internet of Things Journal, 10(3), 1887-1896. https://doi.org/10.1109/jiot.2021.3137408

In [14], a multichannel CSS was proposed for a cognitive sensor network, where the number of sensing users was minimized under the constraints of the global detection probability and false alarm probability. CSS based on soft decision was proposed in [15] to improve CSS performance for hidden PU in fading and shadowing environment, which showed better performance than the hard decision algorithm. To sense multiple channels in a heterogeneous network, multiband multiuser CSS was proposed for a distributed IoT in [16], which was optimized to improve both the detection performance and throughput of the IoT. To identify spectral and spatial resources for an unlicensed IoT, a wideband sensing-based architecture was proposed in [5], which could achieve more spatio-spectral resources with lower misdetection probability. Though improving spectrum sensing accuracy may guarantee the spectrum access performance of the CIIoT, but it will cause large sensing overhead to decrease its transmission performance. Thus, there exists a tradeoff between spectrum sensing accuracy and transmission performance. In [17], a sensing-throughput tradeoff for the CSS was presented to maximize the CR's throughput by optimizing sensing time. In [18], considering the PU's traffic in the sensing-throughput tradeoff model, the transmission performance of the CR significantly degraded when the transmission frequency and signal-to-noise ratio (SNR) of the PU increased. The sensing-throughput tradeoff under random arrivals and departures of multiple PUs was analyzed in [19], where the impacts of the PU's transmission parameters on the tradeoff were also investigated to guarantee the transmission performance of the CR. In [20], an energy-efficient spectrum sensing and transmission scheme was proposed for CR by jointly optimizing sensing and transmission durations. However, the sensing-throughput tradeoff model only optimized the spectrum sensing time without considering the spectrum access control, which cannot avoid causing interference to the PU.

The spectrum access control including transmission power control and interference control will affect the transmission performance of both the CIIoT and PU. The authors in [21] indicated that a robust access control algorithm should be able to obtain reasonably good solutions to ensure the acceptable transmission performance under the worst interference conditions. In [22], by controlling the spectrum access parameters according to the observed PU's signal, the CR system was able to obtain higher transmission performance under the interference limitation to the PU. Dynamic multiobjective optimization was proposed for power and spectrum allocation of CR in [23], which achieved comprehensive performance improvement in terms of energy efficiency, fairness, spectrum utilization, etc. In [24], deep Q network (DQN) was used to allocate proper transmit power for the users in a CR-based industrial cyber-physical system, and the transmit power of each user was calculated by the lower bound of SNR to guarantee its transmission performance. A low-complexity optimal power control scheme was proposed for a CR system in [25], which maximized the achievable rate in the low-power regime by controlling the interference between the CR and PU. In [26], a robust distributed power allocation approach was proposed to maximize the uplink spectrum utilization of the CR, while both the transmission qualities of the CR and PU are guaranteed. In [27], a point-to-multipoint CR network was considered to access multiple channels of a PU network, where the power and channels were jointly allocated to maximize the CR's throughput under the constraint of guaranteeing the PU's communication performance. However, the impacts of spectrum sensing probability on the spectrum access performance were not considered in the traditional access control schemes.

In this paper, integrated CSS and access control is proposed for the CIIoT to maximize its transmission performance, providing that both the performances of spectrum sensing and PU's communication are guaranteed. The main contributions of the paper are summarized as follows.

- An integrated CSS and access control model is proposed for the CIIoT, where the nodes control their spectrum access parameters according to the decision results of the CSS. Such a spectrum decision on the channel state is made at the control center by fusing all the sensing results from the nodes. The frame structure of the model, constituting of spectrum sensing slot, access control slot and communication slot, is designed to perform periodic sensing, control and communications. It can guarantee the efficient utilization of idle channels while controlling the interference to the PU.
- The model optimization is presented to maximize the total throughput of the CIIoT in each frame by jointly optimizing sensing time, the number of sensing nodes and the transmit power for each node under the constraints of the minimum detection probability, the total power control, the interference control, and the minimum rate for each node. The formulated optimization problem is solved using alternating direction optimization (ADO) method [28], which is divided into three suboptimization problems for spectrum sensing, channel allocation and access control, respectively. A joint optimization algorithm of CSS and access control is proposed to achieve the optimal solutions.
- Simultaneous CSS and access control model is proposed to increase the communication time by performing CSS and access control in one time slot. In this model, all the nodes can participate in the CSS to improve the sensing performance without reducing the communication time.

The rest of the paper is organized as follows. The integrated CSS and access control model is described in Section II, where the CSS probabilities and throughput of the CIIoT are analyzed, respectively. In Section III, the model optimization problem is presented to maximize the total throughput of the CIIoT in each frame, which can be solved by a joint optimization algorithm of CSS and access control. A simultaneous CSS and access control model is proposed in Section IV. In Section V, some numerical simulation results are presented and discussed. The conclusions of the paper are finally drawn in Section VI.

II. System Model

A. Integrated cooperative spectrum sensing and access control

Consider a CIIoT network constituting of N communication nodes and one control center can access M channels licensed to the PUs, as shown in Fig. 1. To guarantee each node has one available channel, we suppose $N \ll M$. In the integrated CSS and access control model, each node can sense the PU and exchange the sensing and decision information with the control center. The frame structure of the CIIoT is divided into spectrum sensing slot, access control slot and communication slot, as shown in Fig. 2. The spectrum sensing slot is further divided into M subslots, within each of which the nodes will sense the status information of a single channel. In the access control slot, each node sends its sensing information to the control center, which will then allocate the channel and transmit power for each node according to the fused sensing decisions. To avoid the interference between the CIIoT nodes, one channel is only allocated to one node. If the allocated channel has been detected to be idle, the node can transmit in the communication slot, otherwise, it has to wait for the next frame to be allocated a new free channel. Suppose the time for each frame is T and the sensing time for each channel is τ. The access control time is decided by the receiving sensing capacity, which is proportional to the number of sensing nodes, N_s, where $1 \leq N_s \leq N$. Thus, the control time can be denoted as $t_c = N_s\xi$, where ξ is the unit control overhead. The communication time can be given by $t_p = T - M\tau - N_s\xi$. Obviously, the control time will increase with N_s and thus decrease the communication time. Therefore, N_s should be selected reasonably to obtain a tradeoff between access control and communications.

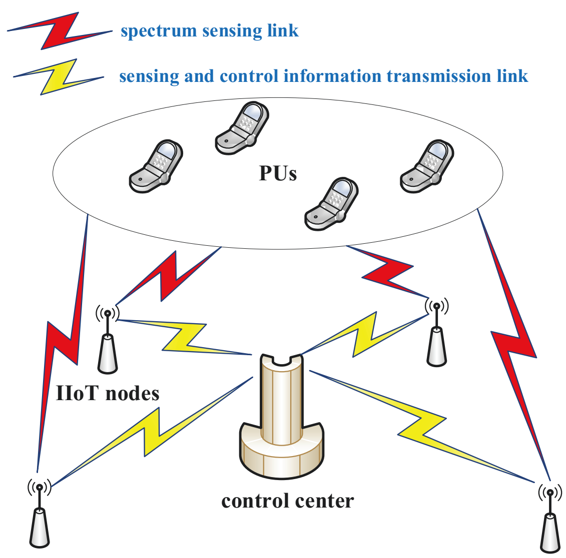

Fig. 1. Integrated CSS and access control model

B. Cooperative spectrum sensing

The spectrum sensing for the PU can be seen as a binary detection problem. The signal in the channel n for $n = 1,2,...,M$ sensed by the node i for $i = 1,2,...,N_s$ is given by

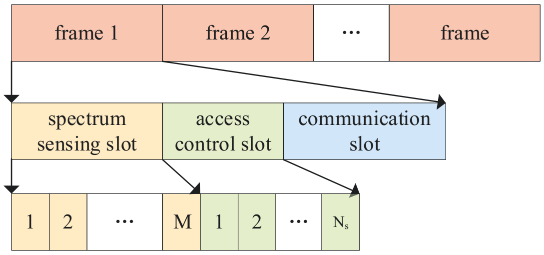

Fig. 2. Frame structure of CIIoT

$$y_i^{[n]}(t) = \theta^{[n]} s^{[n]}(t) h_i^{[n]}(t) + \sigma_0^{[n]}(t) \tag{1}$$

where t is the sampling time, $y_i^{[n]}(t)$ is the sensing signal, $s^{[n]}(t)$ is the PU's signal, $h_i^{[n]}(t)$ is the channel gain between the PU and the node i, and $\sigma_0^{[n]}(t)$ is the noise; $\theta^{[n]}$ is the channel state of channel n, where $\theta^{[n]} = 0$ and $\theta^{[n]} = 1$ denotes the idle channel and busy channel, respectively.

Sometimes one node may be in deep fading channel and will not achieve accurate sensing result. The CSS allows multiple nodes to sense the channel collaboratively, which may still achieve better sensing performance in fading environment if one node has better sensing link. In the CSS, $y_i^{[n]}$ for $i = 1,2,...,N_s$ are sent to the control center by all the sensing nodes. By fusing all the receiving sensing information, the control center use ED to decided the idle or busy state of the channel, which is given by

$$idle: \sum_{t=1}^{t_s}\sum_{i=1}^{N_s} |y_i^{[n]}(t)|^2 \leq \lambda \tag{2}$$

$$busy: \sum_{t=1}^{t_s}\sum_{i=1}^{N_s} |y_i^{[n]}(t)|^2 > \lambda \tag{3}$$

where t_s is the total sampling time and λ is the sensing threshold. By supposing the channel bandwidth is W, we can get $t_s = 2W\tau$.

Substituting (1) to (2) and (3), the false probability probability and detection probability of the CSS can be obtained from the Central Limit Theorem as follows

$$P_f^{[n]} = Q\left(\left(\frac{\lambda}{\delta_n^2} - 1\right)\sqrt{W\tau N_s}\right) \tag{4}$$

$$P_d^{[n]} = Q\left(\left(\frac{\lambda}{\delta_n^2} - \gamma_n - 1\right)\sqrt{\frac{W\tau N_s}{2\gamma_n + 1}}\right) \tag{5}$$

where δ_n^2 is the channel noise power, and $\gamma_n = \frac{1}{T_s N_s}\sum_{i=1}^{N_s}\sum_{t=1}^{t_s}\frac{|s^{[n]}(t)h_i^{[n]}(t)|^2}{\delta_n^2}$ is the average sensing SNR; the function $Q(x)$ is described as follows

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{+\infty} e^{-\frac{x^2}{2}}\mathbf{d}x \tag{6}$$

To guarantee the sensing performance for the PU, the sensing threshold can set according to the detection probability as

$$\lambda = \left(Q^{-1}(P_d^{[n]}) \sqrt{\frac{2\gamma_n + 1}{W\tau N_s}} + \gamma_n + 1 \right) \sigma_n^2 \tag{7}$$

Suppose the actual idle and busy probabilities of the channel n are $P_{\theta_0}^{[n]}$ and $P_{\theta_1}^{[n]}$, respectively, which satisfy $P_{\theta_0}^{[n]} + P_{\theta_1}^{[n]} = 1$. The spectrum access probability of the channel can be given by $P_{acc}^{[n]} = (1 - P_f^{[n]})P_{\theta_0}^{[n]}$. To ensure the communication performance of the CIIoT, the control center preferentially allocates the channels with higher spectrum access probabilities to the nodes. To avoid bringing severe interference to the PU, we order that $P_d^{[n]} \geq P_d^{min}$, where P_d^{min} is the required minimum detection probability. Then from (4) and (7), $P_f^{[n]}$ is expressed by P_d^{min} as follows

$$P_f^{[n]} \geq Q\left(Q^{-1}(P_d^{min})\sqrt{2\gamma_n + 1} + \gamma_n \sqrt{W\tau N_s} \right) \tag{8}$$

where we can further rewrite $P_{acc}^{[n]}$ as follows

$$P_{acc}^{[n]} \leq \left(1 - Q\left(Q^{-1}(P_d^{min})\sqrt{2\gamma_n + 1} + \gamma_n \sqrt{W\tau N_s} \right) \right) P_{\theta_0}^{[n]} \tag{9}$$

To ensure enough spectrum access for each node, we let $P_{acc}^{[n]} \geq P_{acc}^{min}$, where P_{acc}^{min} is the required minimum spectrum access probability. Then we can get

$$Q^{-1}(P_d^{min})\sqrt{2\gamma_n + 1} + \gamma_n \sqrt{W\tau N_s} \geq Q^{-1}\left(1 - \frac{P_{acc}}{P_{\theta_0}^{[n]}} \right) \tag{10}$$

Assume the CIIoT nodes are in fading channels and $\gamma_n \ll 1$. From (10), we can get

$$\gamma_n \geq \frac{Q^{-1}\left(1 - \frac{P_{acc}}{P_{\theta_0}^{[n]}} \right) - Q^{-1}(P_d^{min})}{Q^{-1}(P_d^{min}) + \sqrt{W\tau N_s}} \tag{11}$$

Then only the channels whose SNR satisfying (11) can be allocated to the nodes.

C. Throughput of CIIoT

To avoid causing interference between the nodes, each channel is only allocated to one node. Assuming the transmit power for node n is $p^{[n]}$, the transmit rate of the node is given by

$$r^{[n]} = W\left((1 - P_f^{[n]})P_{\theta_0}^{[n]} \log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2} \right) \right) \tag{12}$$

the total throughput of the CIIoT within the communication slot is given by

$$R = (T - M\tau - N_s\xi)\sum_{n=1}^{N} r^{[n]} \tag{13}$$

When the busy channel has been detected to be idle by mistake, the CIIoT will also access the channel and cause harmful interference to the PU. The total interference power of the CIIoT can be given by

$$p_I = \sum_{n=1}^{N}(1 - P_d^{[n]})P_{\theta_1}^{[n]} p^{[n]}|h^{[n]}|^2 \tag{14}$$

To ensure the transmission performance of the PU, the SNR of the PU must be no less than the minimum SNR, γ_s^{min}, which is defined as

$$\frac{\sum_{n=1}^{N} P_{\theta_1}^{[n]} p_s^{[n]}|h^{[n]}|^2}{\sum_{n=1}^{N}\delta_n^2 + p_I} \geq \gamma_s^{min} \tag{15}$$

where $p_s^{[n]}$ is the average power of the PU in channel n. Then we can get the upper bound of p_I as follows

$$p_I \leq \frac{\sum_{n=1}^{N} P_{\theta_1}^{[n]} p_s^{[n]}|h^{[n]}|^2}{\gamma_s^{min}} - \sum_{n=1}^{N}\delta_n^2 \tag{16}$$

III. Model Optimization

We try to maximize the total throughput of the CIIoT in each frame by jointly optimizing the sensing time τ, the number of sensing nodes N_s and the transmit power vector for the nodes $\{p^{[n]}\}$, subject to the constraints of the minimum detection probability, the total power control, the interference power control and the minimum rate for each node. The optimization problem is formulated as follows

$$\max_{\tau, N_s, \{p^{[n]}\}} \quad R = (T - M\tau - N_s\xi)W \times \sum_{n=1}^{N}\left((1 - P_f^{[n]})P_{\theta_0}^{[n]} \log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2} \right) \right) \tag{17a}$$

$$\text{s.t.} \quad P_d \geq P_d^{min} \tag{17b}$$

$$\sum_{n=1}^{N} p^{[n]} \leq p_{tot} \tag{17c}$$

$$\sum_{n=1}^{N}(1 - P_d^{[n]})P_{\theta_1}^{[n]} p^{[n]}|h^{[n]}|^2 \leq p_I^{max} \tag{17d}$$

$$W\left((1 - P_f^{[n]})P_{\theta_0}^{[n]} \log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2} \right) \right) \geq r_{min}^{[n]} \tag{17e}$$

$$T - M\tau - N_s\xi \geq 0 \tag{17f}$$

$$1 \leq N_s \leq N \tag{17g}$$

$$\tau \geq 0; \quad p^{[n]} \geq 0, n = 1, 2, ..., N \tag{17h}$$

where p_{tot} is the maximum total power of the CIIoT, p_I^{max} is the upper bound of the interference power which is given in (16), and $r_{min}^{[n]}$ is the minimum rate for each node. Equation (17) is a multivariable optimization problem that can be solved using the ADO method.

A. Spectrum Sensing Optimization

First fixing the transmit power vector $\{p^{[n]}\}$, the optimization problem (17) is only related with τ and N_s. Therefore, we may optimize τ and N_s to maximize the throughput. The optimization problem is given by

$$\max_{\tau,N_s} \quad R = W(T - M\tau - N_s\xi)\sum_{n=1}^{N}\left((1-P_f^{[n]})\eta^{[n]}\right) \tag{18a}$$

$$\text{s.t.} \quad P_d \geq P_d^{min} \tag{18b}$$

$$0 \leq \tau \leq \frac{T - N_s\xi}{M} \tag{18c}$$

$$1 \leq N_s \leq N \tag{18d}$$

where $\eta^{[n]} = P_{\theta_0}^{[n]} \log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right)$. To solve (18), we first give Lemma 1.

Lemma 1: The optimization problem (18) can be solved only when $P_d^{[n]} = P_d^{min}$.

Proof: From (4) and (7), as $Q(x)$ is a monotone decreasing function, both $P_f^{[n]}$ and $P_d^{[n]}$ reduce with the increase of λ. Therefore, when $P_d^{[n]} = P_d^{min}$, $P_f^{[n]}$ also achieves its minimum value, which will make the objective function of (18) get its maximum value. Then assume that there is a value $P_d^{[n]} = \hat{P}_d > P_d^{min}$ that makes the objective function of (18) get the maximum value. From (8), we will have $P_f^{[n]}(P_d^{[n]} = \hat{P}_d) > P_f^{[n]}(P_d^{[n]} = P_d^{min})$. Then the value of the objective function with $P_d^{[n]} = \hat{P}_d$ is not the maximum, which is in contradiction with the assumption. Hence, the maximum value of the objective function can be obtained only when $P_d^{[n]} = P_d^{min}$. ∎

Substituting $P_d^{[n]} = P_d^{min}$ into (18), the optimization problem is rewritten as follows

$$\max_{\tau,N_s} \quad R = W(T - M\tau - N_s\xi)\times \sum_{n=1}^{N}\left(\eta^{[n]}\left(1 - Q\left(Q^{-1}(P_d^{min})\sqrt{2\gamma_n+1} + \gamma_n\sqrt{W\tau N_s}\right)\right)\right) \tag{19a}$$

$$\text{s.t.} \quad 0 \leq \tau \leq \frac{T - N_s\xi}{M} \tag{19b}$$

$$1 \leq N_s \leq N \tag{19c}$$

Fixing N_s, we will prove (19) is a convex optimization problem about τ in Lemma 2.

Lemma 2: The objective function of (19) is convex in τ when $P_f^{[n]} \leq 0.5$.

Proof: Assume $T' = \frac{T-N_s\xi}{M}$, $\alpha_n = Q^{-1}(P_d^{min})\sqrt{2\gamma_n+1}$ and $\beta_n = \gamma_n\sqrt{WN_s}$. Then the objective function (19a) is rewritten as

$$R(\tau) = MW(T'-\tau)\sum_{n=1}^{N}\left(\eta^{[n]}\left(1 - Q\left(\alpha_n + \beta_n\sqrt{\tau}\right)\right)\right) \tag{20}$$

Then we will prove that $\hat{r}^{[n]}(\tau) = (T'-\tau)\left(1 - Q\left(\alpha_n+\beta_n\sqrt{\tau}\right)\right)$ is convex in τ. The first-order and second-order partial derivatives of $\hat{r}^{[n]}(\tau)$ are respectively given by

$$\nabla\hat{r}^{[n]}(\tau) = -\left(1 - Q(\alpha_n + \beta_n\tau)\right) + \frac{T'-\tau}{2\sqrt{2\pi\tau}}e^{-\frac{(\alpha_n+\beta_n\sqrt{\tau})^2}{2}} \tag{21}$$

$$\nabla^2\hat{r}^{[n]}(\tau) = 2\nabla P_f^{[n]} - (T'-\tau)\nabla^2 P_f^{[n]} \tag{22}$$

where $\nabla P_f^{[n]}$ and $\nabla^2 P_f^{[n]}$ are the first-order and second-order partial derivatives of $P_f^{[n]}$, respectively, which are given by

$$\nabla P_f^{[n]} = -\frac{\beta_n}{2\sqrt{2\pi\tau}}e^{-\frac{(\alpha_n+\beta_n\sqrt{\tau})^2}{2}} \tag{23}$$

$$\nabla^2 P_f^{[n]} = \frac{\beta_n^2}{4\sqrt{2\pi}\tau}e^{-\frac{(\alpha_n+\beta_n\sqrt{\tau})^2}{2}}\left(\frac{1}{\beta_n\sqrt{\tau}} + \alpha_n + \beta_n\sqrt{\tau}\right) \tag{24}$$

Noting that $0 < Q(\alpha_n + \beta_n\sqrt{\tau}) < 1$, from (21) we can get $\nabla\hat{r}^{[n]}(\tau) < 0$ when $\tau = T'$ and $\nabla\hat{r}^{[n]}(\tau) \to +\infty$ when $\tau = 0$. Therefore, there is a value $\tau = \tau^*$ within $0 \sim T'$ that makes $\nabla\hat{r}^{[n]}(\tau^*) = 0$.

If $P_f^{[n]} = Q\left(\alpha_n + \beta_n\sqrt{\tau}\right) \leq 0.5$, we have $\alpha_n + \beta_n\sqrt{\tau} \geq 0$. Then from (23) and (24) we can get $\nabla P_f^{[n]} < 0$ and $\nabla^2 P_f^{[n]} > 0$. Therefore, from (22) we can get $\nabla^2\hat{r}^{[n]}(\tau) < 0$. Since $\nabla\hat{r}^{[n]}(\tau^*) = 0$ and $\nabla^2\hat{r}^{[n]}(\tau^*) < 0$, $\hat{r}^{[n]}(\tau)$ is convex in τ with its maximum value as $\hat{r}^{[n]}(\tau^*)$.

As $R(\tau) = MW\sum_{n=1}^{N}\eta^{[n]}\hat{r}^{[n]}(\tau)$ is the linear sum of a series of convex functions, $R(\tau)$ is also convex in τ. The optimal solution τ^* should make $\nabla R(\tau^*) = MW\sum_{n=1}^{N}\nabla\hat{r}^{[n]}(\tau^*) = 0$. ∎

The optimal solution of τ can be achieved by the half searching algorithm, which is described in Algorithm 1.

Algorithm 1 Optimization of τ

Initialize: $\tau_{min} = 0$, $\tau_{max} = T'$, and $\tau = \frac{\tau_{min}+\tau_{max}}{2}$;
1: **while** $\tau_{min} \neq \tau_{max}$ **do**
2: if $\nabla R(\tau_{min}) == \nabla R(\tau)$
3: set $\tau_{min} = \tau$;
4: else if $\nabla R(\tau_{max}) == \nabla R(\tau)$
5: set $\tau_{max} = \tau$;
6: set $\tau = \frac{\tau_{min}+\tau_{max}}{2}$;
7: **end while**
Output: $\tau^* = \frac{\tau_{min}+\tau_{max}}{2}$.

Letting $\tau = \tau^*$, the optimization problem (19) about N_s is given by

$$\max_{N_s} \quad R = W(T'' - N_s\xi)\sum_{n=1}^{N}\left(\eta^{[n]}\left(1 - Q\left(\alpha_n + \gamma_n\sqrt{W\tau N_s}\right)\right)\right) \tag{25a}$$

$$\text{s.t.} \quad 1 \leq N_s \leq \min\left\{N, \frac{T''}{\xi}\right\} \tag{25b}$$

where $T'' = T - M\tau^*$. Since N_s is an integer in a finite range, the optimal solution of N_s can be obtained by the enumeration algorithm. The jointly optimal solutions can be obtained by alternatively optimizing τ and N_s until the objective function R is convergent. The joint optimization of τ and N_s is described in Algorithm 2. Assuming the calculation accuracy is δ, the complexity of optimizing τ by half searching is $O(\log\frac{T'}{\delta})$, and the complexity of optimizing N by enumeration searching is N. Supposing the number of iterations for Algorithm 2 is K, the total complexity for Algorithm 2 is $K(O(\log\frac{T'}{\delta}) + N)$.

Algorithm 2 Joint optimization of τ and N_s

Initialize: the optimal solution $\tau^* = 0$ and $N_s^* = 1$;

while R is not convergent **do**

fixing $N_s = N_s^*$, update the optimal τ^* by the Algorithm 1;

fixing $\tau = \tau^*$, update the optimal N_s^* by solving (25) with the enumeration algorithm;

calculate R with the updated N_s^* and τ^*;

end while

Output: $\tau = \tau^*$ and $N_s = N_s^*$.

B. Channel Allocation Optimization

We will select N available channels from the total M channels to assign to the N nodes. The channel allocation scheme should guarantee that each node has higher transmission performance and causes less interference to the PU. Therefore, the allocation basis function is given by

$$\psi^{[n]} = (1 - P_f^{[n]})P_{\theta_0}^{[n]}\frac{|h^{[n]}|^2}{\delta_n^2} - \kappa^{[n]}(1 - P_d^{[n]})P_{\theta_1}^{[n]}|h^{[n]}|^2 \quad (26)$$

where $\kappa^{[n]}$ for $n = 1, 2, ..., N$ are the weight coefficients. The increase of $\psi^{[n]}$ means the improvement of the transmission performance of the CIIoT as well as the decrease of the interference to the PU.

As $P_d^{[n]} = P_d^{min}$, substituting (8) into (26), $\psi^{[n]}$ can be rewritten as follows

$$\begin{aligned}\psi^{[n]} &= \left(1 - Q\left(Q^{-1}(P_d^{min})\sqrt{2\gamma_n + 1} + \gamma_n\sqrt{W\tau N_s}\right)\right) \\ &\times \quad P_{\theta_0}^{[n]}\frac{|h^{[n]}|^2}{\delta_n^2} - \kappa^{[n]}(1 - P_d^{min})(1 - P_{\theta_0}^{[n]})|h^{[n]}|^2 \quad (27)\end{aligned}$$

which is only related with γ_n, $P_{\theta_0}^{[n]}$ and $h^{[n]}$. Therefore, we will calculate $\psi^{[n]}$ for each channel and the first N channels with larger $\psi^{[n]}$ are allocated to the nodes.

C. Access Control Optimization

By fixing $\tau = \tau^*$, $N_s = N_s^*$ and $P_d = P_d^{min}$, from (8) we can get the value of $P_f^{[n]}$ as follows

$$P_f^{[n]*} = Q\left(Q^{-1}(P_d^{min})\sqrt{2\gamma_n + 1} + \gamma_n\sqrt{W\tau^* N_s^*}\right) \quad (28)$$

Then the optimization problem (17) about $p^{[n]}$ is rewritten as follows

$$\max_{\{p^{[n]}\}} \quad R = \phi W \sum_{n=1}^{N}\left((1 - P_f^{[n]*})P_{\theta_0}^{[n]}\log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right)\right) \quad (29a)$$

$$\text{s.t.} \quad \sum_{n=1}^{N} p[n] \le p_{tot} \quad (29b)$$

$$\sum_{n=1}^{N} P_{\theta_1}^{[n]}p^{[n]}|h^{[n]}|^2 \le \frac{p_I^{max}}{1 - P_d^{min}} \quad (29c)$$

$$(1 - P_f^{[n]*})P_{\theta_0}^{[n]}\log\left(1 + \frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right) \ge \frac{r_{min}^{[n]}}{W} \quad (29d)$$

$$p^{[n]} \ge 0, n = 1, 2, ..., N \quad (29e)$$

where $\phi = T - M\tau^* - N_s^*\xi$. From (29d), the lower bound of $p^{[n]}$ can be obtained by

$$p^{[n]} \ge \left(2^{\frac{r_{min}^{[n]}}{W(1-P_f^{[n]*})P_{\theta_0}^{[n]}}} - 1\right)\frac{\delta_n^2}{|h^{[n]}|^2} \quad (30)$$

Equation (29) is an convex optimization problem and satisfies the Karush-Kuhn-Tucker (KKT) conditions. It can be solved by the Lagrange multiplier method. The Lagrange optimization function is given in (30), where $\lambda_1 > 0$ and $\lambda_2 > 0$ are both the Lagrange multipliers. The optimal power $\{p^{[n]*}\}$ can be achieved by $\frac{\partial L}{\partial p^{[n]}} = 0$. Considering the power constraint in (30), $\{p^{[n]*}\}$ can be achieved in (31).

The Lagrange multipliers λ_1 and λ_2 can be obtained by the subgradient method as follows

$$\lambda_1^{(i+1)} = \lambda_1^{(i)} - \nu_1^{(i)}\left(p_{tot} - \sum_{n=1}^{N} p[n]\right)^+ \quad (32)$$

$$\lambda_2^{(i+1)} = \lambda_2^{(i)} - \nu_2^{(i)}\left(\frac{p_I^{max}}{1 - P_d^{min}} - \sum_{n=1}^{N} P_{\theta_1}^{[n]}p^{[n]}|h^{[n]}|^2\right)^+ \quad (33)$$

where i is the iteration index, $\nu_1 > 0$ and $\nu_2 > 0$ are the iterative steps. The power optimization algorithm is shown in Algorithm 3.

Algorithm 3 Optimization of $\{p^{[n]}\}$

Initialize: $\lambda_1^{(i)}$ and $\lambda_2^{(i)}$ with any values greater than 0, $\{p^{[n]*}\} = \{0\}$, $i = 1$;

while any of λ_1 and λ_2 is not convergent **do**

fixing $\lambda_1 = \lambda_1^{(i)}$ and $\lambda_2 = \lambda_2^{(i)}$, update $\{p^{[n]*}\}$ by (31);

fixing $\{p^{[n]}\} = \{p^{[n]*}\}$ and selecting $\nu_1^{(i)}$ and $\nu_2^{(i)}$, update $\lambda_1^{(i+1)}$ and $\lambda_2^{(i+1)}$ by (32) and (33);

set $i = i + 1$;

end while

Output: $\{p^{[n]}\} = \{p^{[n]*}\}$.

Using the ADO, the joint optimization of spectrum sensing and access control is described in Algorithm 4.

Algorithm 4 Joint optimization of spectrum sensing and access control

Initialize: the optimal solution $\tau^* = 0$, $N_s^* = 1$ and $\{p^{[n]*}\} = \{0\}$;

while R is not convergent **do**

fixing $\tau = \tau^*$ and $N_s = N_s^*$, update the optimal $\{p^{[n]*}\} = \{0\}$ by the Algorithm 3;

fixing $\{p^{[n]}\} = \{p^{[n]*}\}$, update the optimal τ^* and N_s^* by the Algorithm 2;

calculate R with updated N_s^*, τ^* and $\{p^{[n]*}\}$;

end while

Output: $\tau = \tau^*$, $N_s = N_s^*$ and $\{p^{[n]}\} = \{p^{[n]*}\}$.

$$L(\{p^{[n]}\},\lambda_1,\lambda_2)=\sum_{n=1}^{N}\left((1-P_f^{[n]*})P_{\theta_0}^{[n]}\log\left(1+\frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right)\right)+\lambda_1\left(p_{tot}-\sum_{n=1}^{N}p[n]\right)+\lambda_2\left(\frac{p_I^{max}}{1-P_d^{[min]}}-\sum_{n=1}^{N}P_{\theta_1}^{[n]}p^{[n]}|h^{[n]}|^2\right) \quad (30)$$

$$p^{[n]*}=\max\left\{\frac{(1-P_f^{[n]*})P_{\theta_0}^{[n]}}{\lambda_1+\lambda_2P_{\theta_1}^{[n]}|h^{[n]}|^2}-\frac{|h^{[n]}|^2}{\delta_n^2},\ \left(2^{\frac{r_{min}^{[n]}}{W(1-P_f^{[n]*})P_{\theta_0}^{[n]}}}-1\right)\frac{|h^{[n]}|^2}{\delta_n^2}\right\},\quad n=1,2,...,N \quad (31)$$

IV. Simultaneous Spectrum Sensing and Access Control

In the above model, spectrum sensing and access control are performed in two independent time slots, and the time for communication slot will be decreased greatly. Therefore, the number of sensing nodes should be optimized to reduce the control time. However, the decrease of the number of sensing nodes will reduce the CSS performance. In this section, we propose a simultaneous spectrum sensing and access control model, where the spectrum sensing and access control are performed in one time slot, as shown in the frame structure of Fig. 3. Since a single access control slot is not needed, all the nodes can participate in the CSS without reducing the transmission time. In the model, each node first senses one channel by ED and makes a local decision immediately in the subslot. The local decision can be 0 or 1, which indicates the idle channel or the busy channel, respectively. Then the control center uses **OR fusion** to combine all the local decisions to get a final decision on the channel states.

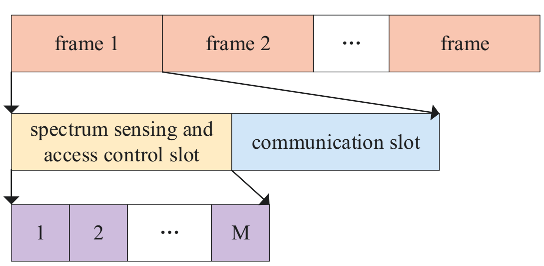

Fig. 3. Frame structure for simultaneous spectrum sensing and access control.

In the ED, the local false alarm probability and detection probability of a single node is given by

$$p_f^{[n]}=Q\left(\left(\frac{\lambda}{\delta_n^2}-1\right)\sqrt{W\tau}\right) \quad (34)$$

$$p_d^{[n]}=Q\left(\left(\frac{\lambda}{\delta_n^2}-\gamma_n-1\right)\sqrt{\frac{W\tau}{2\gamma_n+1}}\right) \quad (35)$$

In the CSS based on **OR fusion**, the idle channel state is finally determined only when all the nodes has detected the absence of the PU in the channel. The false alarm probability and detection probability of CSS are respectively given by

$$P_f^{[n]}=1-(1-p_f^{[n]})^N \quad (36)$$

$$P_d^{[n]}=1-(1-p_d^{[n]})^N \quad (37)$$

Therefore, fixing $P_d^{[n]}=P_d^{min}$, $P_f^{[n]}$ can be denoted by P_d^{min} as follows

$$P_f^{[n]}=1-\left(1-Q\left(Q^{-1}\left(1-(1-P_d^{min})^{\frac{1}{N}}\right)\sqrt{2\gamma_n+1}+\gamma_n\sqrt{W\tau}\right)\right)^N \quad (38)$$

Then the optimization problem to maximize the total throughput of the CIIoT is given as follows

$$\max_{\tau,\{p^{[n]}\}}\ R=(T-M\tau)W\times\sum_{n=1}^{N}\left((1-p_f^{[n]})^NP_{\theta_0}^{[n]}\log\left(1+\frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right)\right) \quad (39a)$$

$$\text{s.t.}\quad 1-(1-p_d^{[n]})^N\geq P_d^{min} \quad (39b)$$

$$\sum_{n=1}^{N}p[n]\leq p_{tot} \quad (39c)$$

$$\sum_{n=1}^{N}(1-p_d^{[n]})^NP_{\theta_1}^{[n]}p^{[n]}|h^{[n]}|^2\leq p_I^{max} \quad (39d)$$

$$W\left((1-p_f^{[n]})^NP_{\theta_0}^{[n]}\log\left(1+\frac{p^{[n]}|h^{[n]}|^2}{\delta_n^2}\right)\right)\geq r_{min}^{[n]} \quad (39e)$$

$$T-M\tau\geq 0 \quad (39f)$$

$$\tau\geq 0;\quad p^{[n]}\geq 0,n=1,2,...,N \quad (39g)$$

The optimization problem (39) can be divided into two suboptimization problems about τ and $\{p^{[n]}\}$, respectively. Like (19) and (29), both of the suboptimization problems are convex and can be solved using the algorithms similar to Algorithm 1 and Algorithm 3. Then a joint optimization algorithm similar to Algorithm 4 can be proposed to achieve the optimal solutions to the optimization problem, as shown in Algorithm 5.

V. Simulations and Discussions

In this section, some numerical simulation results are p-resented and discussed. We set the simulation parameters as follows. The number of channels is $M=30$, the bandwidth of each channel is W=1KHz, the idle channel probability is $P_{\theta_0}^{[n]}=0.5$, the number of CIIoT nodes is $N=20$, the frame period is T=10ms, the unit control overhead is ξ=0.1ms, the maximum interference power is $p_I^{max}=0.1\sim 1$mW, and the maximum total power is $p_{tot}=10\sim 100$mW. The channels

Algorithm 5 Joint optimization of simultaneous spectrum sensing and access control

Initialize: the optimal solution $\tau^* = 0$ and $\{p^{[n]*}\} = \{0\}$;

while R is not convergent **do**

  fixing $\tau = \tau^*$, update the optimal $\{p^{[n]*}\} = \{0\}$ similar with the Algorithm 3;

  fixing $\{p^{[n]}\} = \{p^{[n]*}\}$, update the optimal τ^* similar with the Algorithm 1;

  calculate R with updated τ^* and $\{p^{[n]*}\}$;

end while

Output: $\tau = \tau^*$ and $\{p^{[n]}\} = \{p^{[n]*}\}$.

are modeled as $h = \sqrt{\frac{\theta}{\theta+1}}\tilde{h} + \sqrt{\frac{1}{\theta+1}}\hat{h}$, where $\tilde{h}$ is light-of-sight (LOS) deterministic component, $\hat{h}$ is time-varying Rayleigh fading component and $\theta = 3$ is Rician factor.

Fig. 4 shows the spectrum access probability P_{acc} of the CIIoT with different minimum detection probability P_d^{min}. It illustrates that P_{acc} reduces with the increase of P_d^{min}, which indicates that the maximum spectrum access probability can be achieved only when the detection probability achieve its lower bound. Thus, the simulation result accords with the Lemma 1. Though decreasing P_d^{min} may improve the spectrum access probability but also cause more interference to the PU. To decrease the interference, the total transmission power of the CIIoT has to be controlled, which may decrease the transmission rate. Therefore, the total throughput of the CIIoT will not be high when P_d^{min} is very small. As shown in Fig. 5, there is an optimal $P_d^{min} = 0.9$ that maximizes the total throughput R.

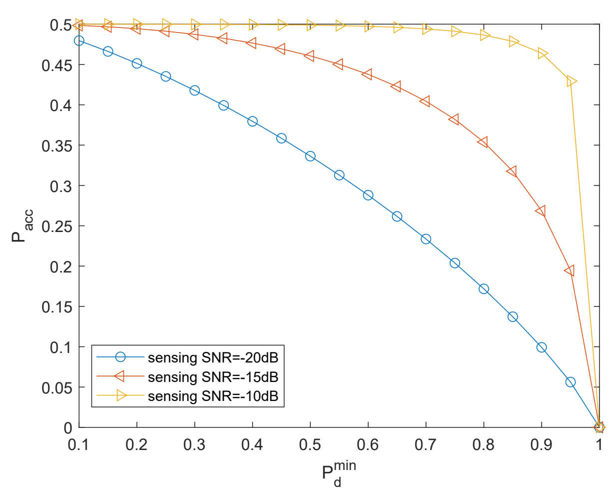

Fig. 4. Spectrum access probability with different minimum detection probability.

Fig. 6 shows that there are optimal sensing time τ and the number of sensing nodes N_s that maximize the total throughput R. It proves the Lemma 2 by the simulation. Fig. 7 illustrates the total throughput with different sensing time. When τ is small, the high false alarm probability may decrease the spectrum access opportunities of the CIIoT, while when τ is large, the long spectrum sensing time will also decrease the

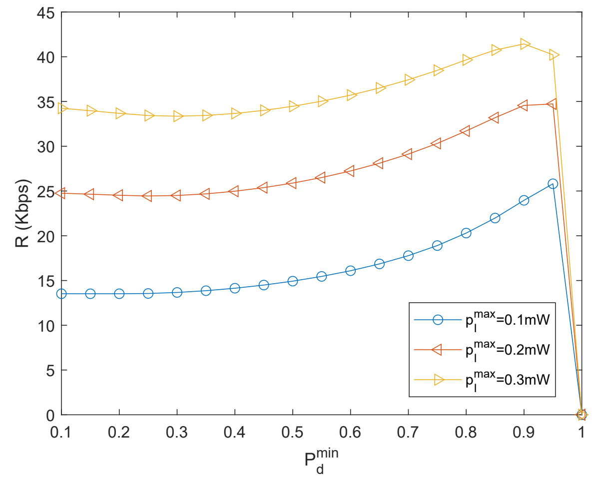

Fig. 5. Total throughput with different minimum detection probability.

communication time. Therefore, both the small τ and large τ will decrease the throughput of the CIIoT, and an optimal τ should be found to maximize the throughput. Fig. 8 shows the total throughput with different number of sensing nodes. When N_s is small, the false alarm probability may increase due to the decreased CSS performance, while when N_s is large, the communication time will decrease due to the increased access control time. Thus, an optimal number of sensing nodes should be selected to maximize the throughput.

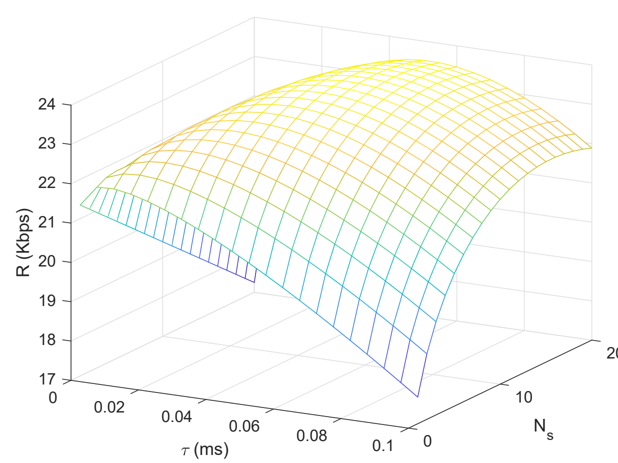

Fig. 6. Total throughput with different sensing time and number of sensing nodes.

Fig. 9 shows the maximum total throughput obtained by the joint optimization algorithm with different sensing SNR. It illustrates that the throughput can be improved by increasing the sensing SNR. Fig. 10 illustrates the maximum total throughput with different maximum interference power p_I^{max}. R reduces with the decrease of p_I^{max}, because the transmit power of the CIIoT is controlled to decrease the interference to the PU. Fig. 11 compares the maximum total throughput between the independent spectrum sensing and access control model and the simultaneous spectrum sensing and access control

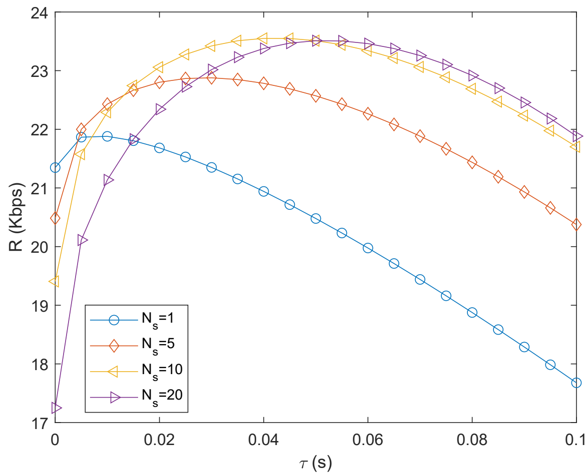

Fig. 7. Total throughput with different sensing time.

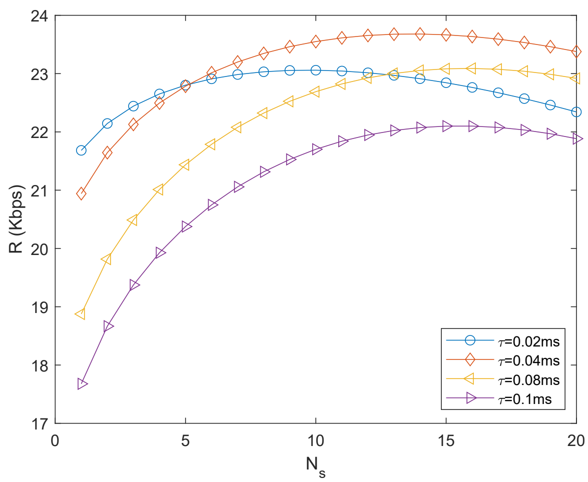

Fig. 8. Total throughput with different number of sensing nodes.

model. It is seen that the simultaneous spectrum sensing and access control model may achieve larger throughput due to the increased communication time.

VI. Conclusions

In this paper, an integrated spectrum sensing and access control model is proposed for the CIIoT to improve its transmission performance while controlling its interference to the PU. This model is optimized to maximize the total throughput of the CIIoT in each frame by jointly optimizing the sensing time, the number of sensing nodes and the transmit power for each node. By ADO, the optimization problem is divided into three suboptimization problems for spectrum sensing, channel allocation and access control, respectively, and it is finally solved by a joint optimization algorithm of spectrum sensing and access control. Through making spectrum sensing and access control performed in one time slot, a simultaneous spectrum sensing and access control mode is proposed to increase the communication time and improve the sensing performance of the CIIoT. The simulation results have shown that there

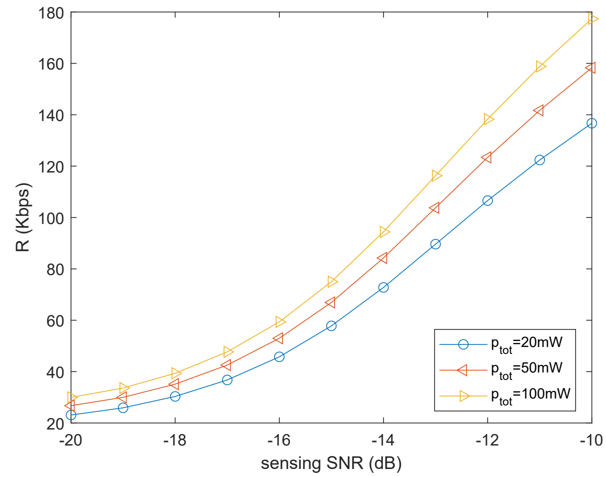

Fig. 9. Maximum total throughput with different sensing SNR.

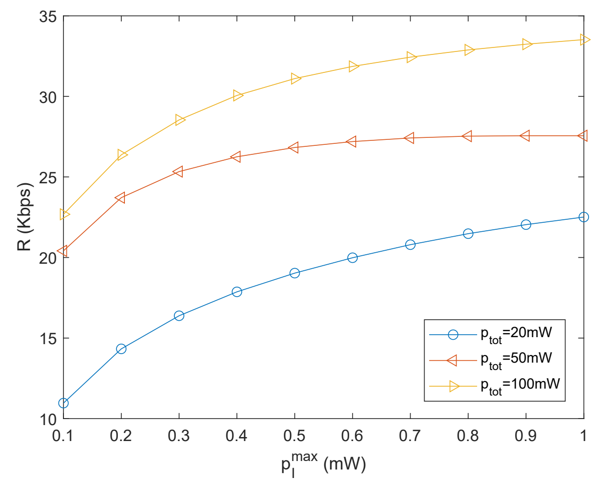

Fig. 10. Maximum total throughput with different maximum interference power.

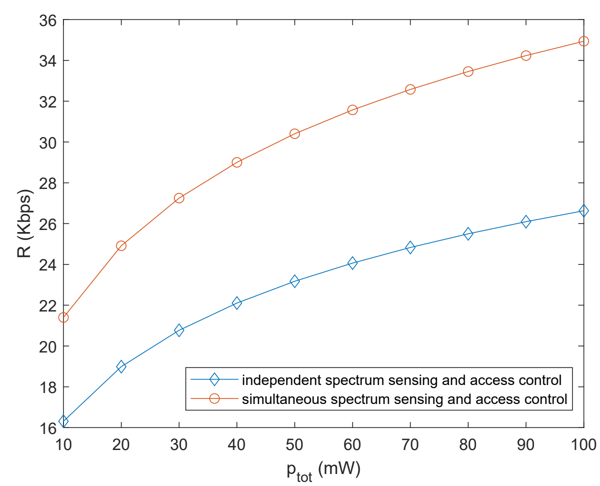

Fig. 11. Maximum total throughput comparison between different spectrum sensing and access control models.

exist optimal sensing and control parameters to maximize the total throughput of the CIIoT under the constraints of spectrum sensing performance and interference control.

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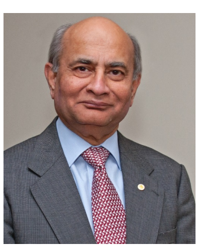
Xin Liu (Senior Member, IEEE) received the M.Sc degree and the Ph.D. degree in Communication Engineering from the Harbin Institute of Technology in 2008 and 2012, respectively. He is currently an Associate Professor with the School of Information and Communication Engineering, Dalian University of Technology, China. From 2012 to 2013, he was a Research Fellow with the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. From 2013 to 2016, he was a Lecturer with the College of Astronautics, Nanjing University of Aeronautics and Astronautics, China. His research interests focus on communication signal processing, cognitive radio, spectrum resource allocation and broadband satellite communications.

Min Jia (Senior Member, IEEE) received the M.Sc. degree in information and communication engineering from Harbin Institute of Technology (HIT), Harbin, China, in 2006, and the Ph.D. degree from the SungKyungKwan University and HIT in 2010. She is currently a Professor and the Ph.D. supervisor with the School of Electronic and Information Engineering, HIT. Her research interests focus on advanced mobile communication technology for LTE and 5G, cognitive radios, digital signal processing, and advanced broadband satellite communication systems.

Prof. Jia has won six best paper awards at several international conferences. She is the General Chair of the IEEE GLOBECOM 2019 Workshopon Intelligent and Cognitive Space, Terrestrial and Ocean Internet, Systems and Applications. She is also a member of the Steering Committee of the WiSATs international conference. She is also the winner of Science Fund for Excellent Young Scholars for Heilongjiang Province and she is elected as a member of National major talent project.

Mu Zhou (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees in the Information and Communication Engineering from the Harbin Institute of Technology (HIT), Harbin, China, in 2006, 2008, and 2012, respectively. He is currently a full Professor in Communication Engineering with the Chongqing University of Posts and Telecommunications (CQUPT), Chongqing, China. He was a Joint-cultivated Ph.D. Student at the University of Pittsburgh (PITT), USA, from 2010 to 2011, and a Post-doctoral Research Fellow at the Hong Kong University of Science and Technology (HKUST), China, from 2012 to 2014. His research interests include the wireless localization and sensing, signal processing and detection, and machine learning and information fusion technologies.

Bin Wang received his Ph.D. degree in Information and Communication Engineering from Xidian University in 2013. He is currently an Associate Professor in School of Communication Engineering, Xian University of Science and Technology. His current research interests include wireless sensor networks, communication signal processing, and image processing.



Tariq S Durrani (Life Fellow, IEEE) a Full Professor with the University of Strathclyde, Scotland, UK, where he was Deputy Principal of the University from 2000 to 2006. He is a Past Vice President of the Royal Society of Edinburgh and the IEEE and a Past President of the IEEE Signal Processing Society and the IEEE Engineering Management Society. He has been the General Chair of several flagship international conferences, including IEEE ICASSP-89, Transputers-91, IEEE IEMC-02, European Universities Convention-06, and IEEE ICC-07. He is a Fellow of the Royal Academy of Engineering, the Royal Society of Edinburgh, the National Academy of Engineering, and the IEEE.