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# Energy-efficiency Maximization for Cooperative Spectrum Sensing in Cognitive Sensor Networks

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***Abstract*—Spectrum sensing is the prerequisite of opportunistic spectrum access in cognitive sensor networks (CSNs) as its reliability determines the success of transmission. However, spectrum sensing is an energy-consuming operation that needs to be minimized for CSNs due to resource limitations. This paper considers the case where the cognitive sensors cooperatively sense a licensed channel by using the CoMAC-based cooperative spectrum sensing (CSS) scheme to determine the presence of primary users. Energy efficiency (EE), defined as the ratio of the average throughput to the average energy consumption, is a very important performance metric for CSNs. We formulate an EE-maximization problem for CSS in CSNs subject to the constraint on the detection performance. In order to address the non-convex and non-separable nature of the formulated problem, we first find the optimal expression for the detection threshold and then propose an iterative solution algorithm to obtain an efficient pair of sensing time and the length of the modulated symbol sequence. Simulations demonstrate the convergence and optimality of the proposed algorithm. It is also observed in simulations that the combination of the CoMAC-based CSS scheme and the proposed algorithm yields much higher EE than conventional CSS schemes while guaranteeing the same detection performance.**

***Index Terms*—Cognitive radio, spectrum sensing, multiple-access channel, analog computation, energy efficiency.**

## I. Introduction

WITH respect to the significant growth in request for wireless services and the scarcity of the spectrum resources, cognitive radio (CR) technology which allows the secondary users (SUs) to access the vacant licensed spectrum of the primary users (PUs) in an opportunistic way, has been proposed [1]-[2]. Spectrum sensing functions have been frequently considered as important components in existing CR approaches, such as [3]-[5]. However, due to the presence of noises and fading of wireless channels, hidden terminals, obstacles, and so on, spectrum sensing of individual nodes cannot achieve high detection accuracies [6]-[7]. In contrast, cooperative spectrum sensing (CSS) exploits a parallel fusion sensing architecture in which independent secondary users (SUs) transmit their sensing data to a fusion center in different time slots based on a time division multiple access (TDMA) scheme [8]-[15] or a random access scheme [16]-[17], due to the extremely limited bandwidth of the common control channel[1]. The fusion center then makes a final soft or hard decision regarding the presence or absence of PUs. The cooperative gains in spectrum sensing performance have been extensively demonstrated in existing works [6]-[17]. However, the drawback of CSS schemes is that both the energy consumption and the reporting time grow linearly with the number of cooperative SUs. Our recent work [18] proposed a time-efficient CSS scheme that takes advantage of the computation over multiple-access channel (CoMAC) method [19] to accelerate the CSS process via merging the reporting and the computation steps of CSS, which noticeably reduces the reporting delay in conventional CSS schemes. However, the issue of high energy consumption still exists due to the fact that each SU has to send a long sequence of encoded symbols to the fusion center during the CSS process.

In this paper, we are interested in the problem of CSS in cognitive sensor networks (CSNs) [20] that are referred to as wireless networks of low-power radios gaining secondary spectrum access according to the CR paradigm previously discussed. CSNs can be particularly used in industrial sensor networks [21] which have recently been considered as an opportunity to realize reliable and low-cost remote monitoring systems for smart grids [22], and their performance has been investigated for various application domains of smart grids in [23]. The cognitive sensors (CSs) of CSNs are typically powered by batteries, which must be either replaced or recharged when or before out of energy. However, it is not always possible to renew or recharge the powers of CS nodes, such as those in unapproachable or hazard zones, which would simply be discarded once their energy sources are depleted.

Motivated by the above discussion, this paper adopts the CoMAC-based CSS scheme due to its high time efficiency for CSNs. To reduce the energy consumption of the CoMAC-based CSS scheme, we propose the joint optimization of the sensing time, the detection threshold and the length of symbol sequence to maximize the energy efficiency (EE) of CSNs. By considering all possible scenarios between PUs

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[1]Notice that, in some cases, such as those in [7], a dedicated control channel is not mandatory for reporting the sensing results in the conventional CSS schemes.

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and CSs, we define the EE of the CSN as the ratio of the average throughput to the average energy consumption. Due to the complicated expression of the EE, the formulated EE-maximization problem is non-convex and non-separable with respect to the optimization variables and thus difficult to solve for global optimality. To address this issue, we first find an optimal expression for the detection threshold by rigorous proof and then propose an iterative solution algorithm (ISA) to obtain an efficient pair of the sensing time and the length of the modulated symbol sequence. Specifically, for a given length of symbol sequence, we prove the quasi-convexity of the EE-maximization subproblem in terms of the sensing time and propose a bisection-based solution algorithm to solve it. Then, provided the newly computed sensing time, we find the optimal length of symbol sequence to the EE-maximization subproblem by using exhaustive search. The above procedure repeats until convergence. The major contributions of this paper are summarized as follows:

- For the CoMAC-based CSS scheme, we for the first time formulate an EE-maximization problem using the sensing time, the detection threshold and the length of symbol sequence as variables to jointly maximize the EE of CSNs while giving adequate protection to the PUs.
- By observing that the PU protection constraint is always tight in the optimal condition, we achieve a closed-form expression for the optimal detection threshold. Further, by eliminating the optimal detection threshold, we arrive at a simplified but equivalent form of the original EE-maximization problem.
- We propose an ISA to the simplified EE-maximization problem. In spite of the non-convex and non-separable nature of the EE-maximization problem, it is shown in simulations that the proposed ISA is not sensitive to the initial value of variables and always converges to the same maximum EE.

The rest of this paper is organized as follows. Section II reviews the related works of this paper. Section III first gives out the system model and then briefly illustrates the CoMAC-based CSS scheme. In Section IV, the EE expression of the CoMAC-based CSS scheme is presented and an EE-maximization problem subject to the constraints of protecting PUs is formulated. In Section V, we present the ISA to solve the EE-maximization problem. Simulation results and conclusions are provided in Section VI and Section VII, respectively.

## II. Related work

In the literature, there are various energy-efficient CSS schemes [20]-[32] to reduce the energy consumption during the CSS process. Maleki et al. [20] proposed a censoring-based CSS scheme for CSNs and optimized the censoring thresholds to minimize the energy consumption while considering the constraints on the detection accuracy. Deng et al. [24] reduced sensing energy consumption via partitioning the set of the SUs into several subsets and activating one subset at certain period. Najimi et al. [25]-[26] proposed an algorithm to divide the second users into subsets. Only the subset that has the lowest cost function (while the cost function is represented by the total energy consumption) and guarantees the desired detection accuracy is selected while the other subsets enter a low power mode. Unlike previous works [20]-[26] whose optimization objectives were to minimize the energy consumptions of spectrum sensing, Monemian et al. [27] and Najimi et al. [28] proposed the sensor selection method for CSS in CSNs with the aim of energy balancing or lifetime maximization. Feng et al. [29] proposed an energy-aware utility function to strike a balance between energy consumption and system throughput. The utility function was maximized by optimizing the sensing time subject to the constraints of sufficient protection for PUs. Huang et al. [30] proposed a novel metric-average sensing energy efficiency measured in [dB/Joule/SU] to evaluate the tradeoff between sensing gain and energy consumption. The metric was then maximized by optimizing the number of SUs. Peh et al. [31] for the first time defined the EE as the average successfully transmitted data normalized by the energy consumption, and optimized the sensing parameters in order to maximize the EE of cognitive radio networks. Althunibat et al. [32] proposed an objection-based CSS scheme which highly reduced the number of reporting SUs via arranging one SU to broadcast its local decision among the whole network and maximized the EE of the objection-based CSS scheme by optimizing the selection of the broadcasting SU. More related works can be found in a recent survey by Althunibat et al. [33].

Based on the the spirits of conventional energy-efficient CSS schemes [16]-[25], this paper proposes to maximize EE of the CSS scheme while preserving PU protection constraints. There are mainly three differences between this paper and conventional CSS schemes [20]-[32].

- First, this paper performs an EE-maximization for the CoMAC-based CSS scheme which is a soft decision in nature, while [20]-[32] optimize the sensing parameters of CSS schemes that are based on the hard decision fusion rule ("$K$-out-of-$N$").
- Second, the EE expression of the studied CSS scheme is much more complicated than metrics of the existing ones, which leads the formulated EE-maximization difficult to solve for global optimality due to its non-convex and non-separable nature.
- Third, unlike the solution methods in conventional CSS schemes [20]-[32], this paper proposes to decouple the EE-maximization problem via mathematical decomposition into two separated subproblems and to solve each of them iteratively until convergence. One subproblem is the sensing time optimization problem that is shown quasi-convex and solved by a bisection-based solution algorithm. The other subproblem is the sequence length optimization problem that is in nature an integer programming and solved by one-dimensional exhaustive search.

## III. System Model and CoMAC-based Cooperative Spectrum Sensing

We consider a single-hop infrastructure CSN with $M$ CSs, one fusion center, one control channel and one licensed

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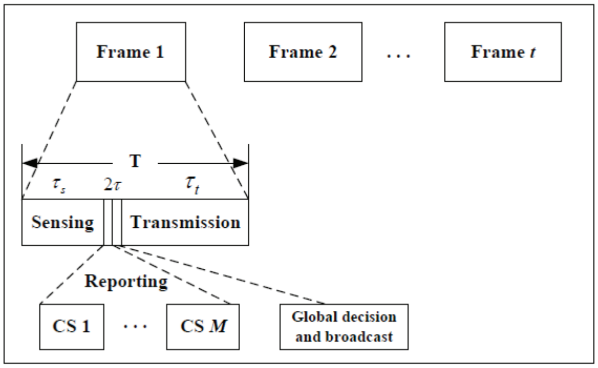


Fig. 1. The time frame architecture for the periodic spectrum sensing.

channel with bandwidth $W$ Hz. It is assumed that all CSs are homogeneous. The time period is partitioned into frames and all nodes are synchronized with the fusion center[2]. Each frame is designed with the periodic spectrum sensing for the CSN. Fig. 1 shows that the frame structure consists of three phases: a sensing phase, a reporting phase, and a transmission phase. In the sensing phase, all cooperative CSs perform spectrum sensing via energy detection. In the reporting phase, the local sensing data at each CS is reported to the fusion center in the form of a sequence of power encoded symbols. Then, the fusion center makes the global decision with respect to received local sensing results according to a given detection threshold and broadcasts the global decision over the control channel at the end of the reporting phase. The CSN selects a narrow band unlicensed spectrum as the control channel which is contention-free but may suffer a flat-fading process. The time for decision fusion and broadcast at the fusion center is fixed and we set the time as one reporting time unit (or mini-slot) for simplicity in the following analysis. The transmission phase is slotted. In the transmission phase, the transmissions of CSs are scheduled by a TDMA-MAC protocol if the PUs are detected absent by the end of the reporting phase. Specifically, at the beginning of the transmission phase, the schedule of data transmission is centrally performed and broadcast by the fusion center over the control channel. After retrieving the schedule, each CS transmits their data to the fusion center in the allocated time slot and falls asleep for the rest of time. Let $\tau_s$ and $\tau_t$ denote the lengths of the sensing phase and the transmission phase, respectively, and let $\tau$ denote one mini-slot length in the reporting phase. Then one frame length is given by $T = \tau_s + 2\tau + \tau_t$. It is possible that PUs are inactive during the spectrum sensing time, but later become active during the following transmission time. However, the probability of this event is negligible due to low spectrum utilization rate of PUs and short duration of the periodic spectrum sensing. To make the analysis tractable as well as focus on the intrinsic feature of the studied problem, we make an assumption to limit the state of the PUs to be fixed within one frame. For notational convenience, we drop the time index and consider an arbitrary frame.

[2]As the studied CSN is fully centralized, all nodes synchronize to the fusion center when they join the network. After the joining process, the synchronization among all nodes can be achieved from the periodic broadcast of global decision by the fusion center.

In the rest of this section, we will briefly introduce the CoMAC-based CSS scheme.

### A. Spectrum Sensing

The local spectrum sensing problem at each CS, say $i$ ($i = 1,2,\ldots,M$ ), can be formulated as a binary hypothesis between the following two hypothesis:

$$\begin{cases} \mathscr{H}_0 : y_i(n) = u_i(n), \ n = 1,2,...,N \\ \mathscr{H}_1 : y_i(n) = h_i(n)s(n) + u_i(n), \ n = 1,2,...,N, \end{cases} \tag{1}$$

where $\mathscr{H}_0$ and $\mathscr{H}_1$ denote the PUs are absent and present on the licensed channel, respectively. $N = \tau_s f^s$ denotes the number of samples, where $f^s$ represents the sampling frequency of CSs. $y_i(n)$ represents the received signal at the CS $i$. $s(n)$ is the PU signal whose power is $\sigma_s^2$. The channel gain $|h_i(n)|$ is assumed Rayleigh-distributed with the same variance $\sigma_h^2$. $u_i(n)$ represents the circular symmetric complex Gaussian noise with mean 0 and variance $\sigma_u^2$. Assume that $s(n)$, $u_i(n)$, and $h_i(n)$ are independent of each other, and the average received SNR at each CS is given as $\gamma = \frac{\sigma_h^2 \sigma_s^2}{\sigma_u^2}$. For spectrum sensing, CS $i$ then uses the average of energy content in received samples as the test statistic for energy detector, which is given by

$$\psi_i(y) = \frac{1}{N} \sum_{n=1}^{N} |y_i(n)|^2.$$

With data fusion, the global test statistic used for final decision at the fusion center is then represented as

$$T_s^{all}(y) = \sum_{i=1}^{M} T_i(y), \tag{2}$$

where $T_i(y) = g_i \psi_i(y)$ is the local statistic of the CS $i$ and $g_i \geq 0$ is the weighting factor associated with CS $i$. Without loss of generality, we assume $\sum_{i=1}^{M} g_i = 1$.

### B. Reporting Phase

Conventionally, in order to compute $T_s^{all}(y)$, the fusion center has to collect $T_i(y)$ from CSs successively. We observe that the transmission of $T_i(y)$ and the computation of $T_s^{all}(y)$ in conventional CSS schemes are separate in the time domain. Such separation-based computation schemes are generally inefficient as a complete reconstruction of individual $T_i(y)$ at the fusion center is unnecessary to compute $T_s^{all}(y)$. In contrast, this paper proposes to merge the process of $T_i(y)$ transmission and $T_s^{all}(y)$ computation via exploiting the CoMAC scheme, which takes only one time unit of the reporting phase.

In the reporting phase, CS $i$ transmits a distinct complex-valued symbol sequence at a transmit power that depends on the the value of $T_i(y)$. Specifically, the transmit power of CS $i$ is $P_i(T_i(y)) = \frac{P_{max}(T_i(y) - x_{min})}{x_{max} - x_{min}}$, where $P_{max}$ represents the transmit power constraint on each CS and $[x_{min}, \ x_{max}]$ ($x_{min} < x_{max}$) denotes the sensing range in which the CSs are able to quantify values. For example, a low-power temperature sensor [34] operates in a typical sensing range $[-55^oC, 130^oC]$. For

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notation convenience, we define $\alpha_{arit} = \frac{P_{max}}{x_{max}-x_{min}}$. Each CS then independently generates a sequence of random transmit symbols with length $L$. Let $\mathbf{S}_i := (S_i[1], S_i[2], ..., S_i[L])^T$ with $S_i[m] = e^{\mathbf{i}\theta_i[m]} (m = 1, 2, ..., L)$ denote the sequence of CS $i$, where $\mathbf{i}$ denotes the imaginary unit and $\{\theta_i[m]\}_{i,m}$ are continuous random phases that are independent identically and uniformly distributed on $[0, 2\pi)$. Then the $m$-th transmit symbol of CS $i$ takes the form

$$\Gamma_i[m] = \frac{\sqrt{P_i(T_i(y))}}{|H_i[m]|} S_i[m], \tag{3}$$

where $|H_i[m]|$ denotes the channel magnitude of an independent complex-valued flat fading process between CS $i$ and the fusion center. We assume the channel gain $H_i[m]$ does not change within one frame length. Therefore, we have $H_i[m] = H_i$, $m = 1, 2, \ldots, L$. It has been reported in [35] that the channel magnitude $|H_i|$ at the transmitter is sufficient to achieve the same performance as with full channel state information. Notice that, the channel inversion in (3) may lead to significant energy consumption especially when the fading is severe. Therefore, we adopt a weighed sum of data fusion by setting

$$g_i = \frac{|H_i|^2}{\sum_{i=1}^{M} |H_i|^2}.$$

In practical systems $\{|H_i|, g_i\}_M$ can be obtained by the fusion center through channel training and estimation, and together with the global decision is broadcast by the fusion center periodically. In doing so, small weights will be assigned to the CSs who suffer severe fading and their transmit powers can be significantly saved. When $g_i = \frac{1}{M}$ $(i = 1, 2, \ldots, M)$, this work becomes the CoMAC-based CSS scheme in [18]. Without loss of generality, we take [18] as an example and study its EE-maximization problem in the rest of this paper.

Concurrent transmission of CSs yields the output at the fusion center

$$\mathbf{Y} = \sum_{i=1}^{M} \sqrt{P_i(T_i(y))} \mathbf{S}_i + \mathbf{U}, \tag{4}$$

where $\mathbf{Y} := (Y[1], Y[2], ..., Y[L])^T \in \mathbb{C}^L$ represents the output vector at the fusion center, and $\mathbf{U} := (U[1], U[2], ..., U[L])^T \in \mathbb{C}^L$ represents an independent stationary complex Gaussian noise vector.

By estimating the energy of signal (4), i.e., $\|\mathbf{Y}\|_2^2$, the fusion center computes an unbiased and consistent estimate $\hat{f}_L(\mathbf{T}(y))$ of the overall test statistic $T_s^{all}(y)$ for spectrum sensing, where $\mathbf{T}(y) = [T_1(y), T_2(y), \ldots, T_M(y)]$. Specifically, $\hat{f}_L(\mathbf{T}(y))$ is given as follows [18]:

$$\hat{f}_L(\mathbf{T}(y)) := \frac{1}{M\alpha_{arit}} \left( \frac{\|\mathbf{Y}\|_2^2}{L} - \sigma_u^2 \right) + x_{min}. \tag{5}$$

To make the final decision, the fusion center compares $\hat{f}_L(\mathbf{T}(y))$ with a threshold $\varepsilon_s$. The PUs are estimated to be absent if $\hat{f}_L(\mathbf{T}(y)) < \varepsilon_s$, or present otherwise.

The detection probability and the false alarm probability of the CoMAC-based CSS scheme are given by [18]

$$P_d = Q\left( \frac{M\alpha_{arit}\left(\varepsilon_s - (1+\gamma)\sigma_u^2\right)}{\sqrt{\frac{\Omega_1(M-1+2\sigma_u^2)+\sigma_u^4}{L} + \frac{M\alpha_{arit}^2\sigma_u^4(2\gamma+1)}{2W\tau_s}}} \right) \tag{6}$$

$$P_f = Q\left( \frac{M\alpha_{arit}\left(\varepsilon_s - \sigma_u^2\right)}{\sqrt{\frac{\Omega_0(M-1+2\sigma_u^2)}{L} + \frac{M\sigma_u^4\alpha_{arit}^2}{2W\tau_s}}} \right) \tag{7}$$

where $Q(x)$ is the complementary distribution of the standard Gaussian, $\Omega_0 = M\alpha_{arit}(\sigma_u^2 - x_{min})$ and $\Omega_1 = M\alpha_{arit}((\gamma+1)\sigma_u^2 - x_{min})$.

In this paper, we do not model the impact of wireless fast fading (e.g., Rayleigh or Rician fading), which enables us to gain insights into the EE-maximization problem while maintaining the solution to the formulated problem sufficiently tractable. The extension of the model in (3) to capture wireless fading will be considered in our future works. Relevant results published in the recent work [35] which combats fast fading by equipping the fusion center with multiple antennas and some statistical channel knowledge will be useful for these further studies.

## IV. Problem Formulation

In this section, we study the relationship between energy consumption and achievable throughput of the CSN. There are four possible scenarios between the activities of PUs and CSs.

Scenario 1: PUs are absent and CSs detect them correctly. In this scenario, the data of CSs are transmitted after spectrum sensing. The energy cost $C_1$ and the throughput $F_1$ of Scenario 1 are given as follows:

$$C_1 = M(E_s\tau_s + LE_t\nu) + E_t(T - 2\tau - \tau_s) \tag{8}$$

$$F_1 = \frac{T - 2\tau - \tau_s}{T} C_0 \tag{9}$$

where $E_s$ and $E_t$ denote the sensing power and the transmit power, respectively. $\nu$ denotes the symbol duration. $C_0$ is the throughput of the CSN if CSs are allowed to continuously operate over the licensed channel in the case of $\mathscr{H}_0$.

Scenario 2: PUs are absent and CSs detect them as present (false alarm happens). In this scenario, the transmissions of CSs are refrained and thus the throughput $F_2$ is 0. The energy cost $C_2$ of Scenario 2 is given as follows:

$$C_2 = M(E_s\tau_s + LE_t\nu). \tag{10}$$

Scenario 3: PUs are present and CSs detect them successfully. In this scenario, the transmissions of CSs are also refrained. Both the energy cost $C_3$ and the throughput $F_3$ of Scenario 3 are the same as those of Scenario 2, i.e., $C_3 = C_2$ and $F_3 = F_2$.

Scenario 4: PUs are present and CSs fail to detect them. In this scenario, the transmissions of CSs are allowed due to the mis-detection. The energy cost $C_4$ of Scenario 4 is the same as that of Scenario 1, i.e., $C_4 = C_1$. Let $\hat{C}_0$ denote the throughput of the CSN in the case of $\mathscr{H}_1$. Then the throughput $F_4$ of Scenario 4 is given as follows:

$$F_4 = \frac{T - 2\tau - \tau_s}{T} \hat{C}_0. \tag{11}$$

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Let $\Pr(\mathscr{H}_i)$ ($i$=0,1) denote the probability of $\mathscr{H}_i$. The probabilities of Scenarios 1-4 are given by $P_1 = \Pr(\mathscr{H}_0)(1-P_f)$, $P_2 = \Pr(\mathscr{H}_0)P_f$, $P_3 = \Pr(\mathscr{H}_1)P_d$ and $P_4 = \Pr(\mathscr{H}_1)(1-P_d)$. Then, the average energy cost within a frame can be constructed as

$$\begin{aligned}&\hat{C}(\tau_s,\varepsilon_s,L)\\&=M(E_s\tau_s+LE_t\nu)+(P_1+P_4)(T-2\tau-\tau_s)E_t. \qquad (12)\end{aligned}$$

Similar to [3], we assume $\Pr(\mathscr{H}_1) < 0.5$ (say less than 0.3, e.g., 0.2 is selected in Section VI), $P_f < 0.5$ and $P_d > 0.5$, which can represent most of typical CR scenarios. Otherwise, it is not economically advisable to explore the secondary usage of the licensed band. As a result, we have $P_4 \ll P_1$. Then, we approximate $\hat{C}(\tau_s,\varepsilon_s,L)$ as

$$\begin{aligned}&C(\tau_s,\varepsilon_s,L)\\&=M(E_s\tau_s+LE_t\nu)+\Pr(\mathscr{H}_0)(1-P_f)(T-2\tau-\tau_s)E_t. \qquad (13)\end{aligned}$$

The average throughput of the CSN can be calculated by

$$\hat{F}(\tau_s,\varepsilon_s,L) = \frac{T-2\tau-\tau_s}{T}(C_0P_1+\hat{C}_0P_4). \qquad (14)$$

The operation of the CSN during the secondary scenario experiences interference from the primary user, and hence, we have $\hat{C}_0 < C_0$. Under the consideration of $\hat{C}_0 < C_0$ and $P_4 \ll P_1$, the first part of $\hat{F}(\tau_s,\varepsilon_s,L)$ dominates the second part of $\hat{F}(\tau_s,\varepsilon_s,L)$. Thus, $\hat{F}(\tau_s,\varepsilon_s,L)$ can be approximated by

$$F(\tau_s,\varepsilon_s,L) = \frac{T-2\tau-\tau_s}{T}C_0P_1. \qquad (15)$$

Finally, the EE of the CoMAC-based CSS scheme $\xi(\tau_s,\varepsilon_s,L)$ is defined as the ratio of the average throughput to the average energy consumption, i.e.,

$$\xi(\tau_s,\varepsilon_s,L) = \frac{F(\tau_s,\varepsilon_s,L)}{C(\tau_s,\varepsilon_s,L)}. \qquad (16)$$

The EE is widely considered as a comprehensive metric that is able to represent the overall performance of a CSN, since it jointly takes into account the achievable throughput, the overall energy consumption and the sensing accuracy.

The objective of this paper is to identify the optimal sensing parameters $(\tau_s,\varepsilon_s,L)$ such that the EE of the CoMAC-based CSS scheme is maximized while the PUs are sufficiently protected. Let $\omega$ denote a pre-specified threshold that is close to but less than 1. For a given $\omega$, the EE-maximization problem can be formulated as follows:

$$\max_{\tau_s,\varepsilon_s,L} \ \xi(\tau_s,\varepsilon_s,L) \qquad (17a)$$

$$s.t. \ P_d(\tau_s,\varepsilon_s,L) \geq \omega, \qquad (17b)$$

$$0 \leq \tau_s \leq T-2\tau, \qquad (17c)$$

$$\varepsilon_s \geq 0, \qquad (17d)$$

$$L_{lower} \leq L \leq L_{max}, \qquad (17e)$$

where $L_{lower}$ and $L_{max}$ denote the lower bound and the upper bound of $L$, respectively. $L_{lower}$ is given according to the required approximation accuracy (such as $L_{lower} = 200$ for the accuracy level of $10^{-2}$ [18]). Taking IEEE 802.15.4 physical layer whose one symbol time is $\nu = 16\mu$s (symbol rate = 62.5 kbaud) as an example [36], we calculate the maximum number of symbols $L_{max}$ during one reporting mini-slot by $L_{max} = \frac{\tau}{\nu} = 625$.

Due to the integer nature of variable $L$ and the complex expressions of $P_d$ and $P_f$ in (6) and (7), problem (17) is obviously non-convex, and a high degree of coupling exists among optimization variables $\{\tau_s,\varepsilon_s,L\}$.

## V. Spectrum Sensing Optimization

In this section, we will first find the optimal detection threshold $\varepsilon_s$ and then propose an iterative solution algorithm (ISA) to find an efficient pair of sensing time $\tau_s$ and sequence length $L$.

### A. Detection Threshold Optimization

*Lemma 1:* Suppose an optimal solution of problem (17) exists, denoted as $(\tau_s^*,\varepsilon_s^*,L^*)$, where $*$ symbol denotes optimality. Then, we have

$$\varepsilon_s^*(\omega) = (1+\gamma)\sigma_u^2 + \frac{\sqrt{\frac{\Omega_1(M-1+2\sigma_u^2)+\sigma_u^4}{L^*}+\frac{M\alpha_{arit}^2\sigma_u^4(2\gamma+1)}{2W\tau_s^*}}Q^{-1}(\omega)}{M\alpha_{arit}}. \qquad (18)$$

*Proof:* We first give out the partial derivative of $\xi(\tau_s,\varepsilon_s,L)$ with $\varepsilon_s$,

$$\frac{\partial\xi(\tau_s,\varepsilon_s,L)}{\partial\varepsilon_s} = -\frac{\partial P_f}{\partial\varepsilon_s}\Delta, \qquad (19)$$

where $\Delta = \frac{T-2\tau-\tau_s}{TC^2(\tau_s,\varepsilon_s,L)}C_0\Pr(\mathscr{H}_0)M(E_s\tau_s+LE_t\nu)$. According to (7), we conclude that $P_f$ is monotonic decreasing in $\varepsilon_s$, i.e., $\frac{\partial P_f}{\partial\varepsilon_s} < 0$, which further implies that $\frac{\partial\xi(\tau_s,\varepsilon_s,L)}{\partial\varepsilon_s} > 0$.

For any given $\tau_s$ and $L$, we can choose a detection threshold $\varepsilon_0$ according to (6) such that $P_d(\varepsilon_0,\tau_s,L) = \omega$. We may also choose a detection threshold $\varepsilon_1 < \varepsilon_0$ such that $P_d(\varepsilon_1,\tau_s,L) > P_d(\varepsilon_0,\tau_s,L)$ and $P_f(\varepsilon_1,\tau_s,L) > P_f(\varepsilon_0,\tau_s,L)$. In doing so, we have $\xi(\varepsilon_1,\tau_s,L) < \xi(\varepsilon_0,\tau_s,L)$. Therefore, the optimal solution to problem (17) $(\varepsilon_s^*,\tau_s^*,L^*)$ must be achieved when the equality constraint in (17b) is fulfilled, i.e., $P_d(\varepsilon_s^*,\tau_s^*,L^*) = \omega$. By expanding the $P_d(\varepsilon_s^*,\tau_s^*,L^*)$, we achieve $L^*M\alpha_{arit}(\varepsilon_s^* - (1+\gamma)\sigma_u^2) = Q^{-1}(\omega)\left(\sqrt{L^*\Omega_1(M-1+2\sigma_u^2)+L^*\sigma_u^4+\frac{(L^*)^2M\alpha_{arit}^2\sigma_u^4(2\gamma+1)}{2W\tau_s^*}}\right)$, which further completes the proof after mathematical simplification. ■

*Remark 1:* From (18), we conclude that $\varepsilon_s^*(\omega)$ is independent with the active probability of primary users $\Pr(\mathscr{H}_1)$, but an increasing function of the received SNR $\gamma$ at each CS. With the increase of $\gamma$ and $\varepsilon_s^*(\omega)$, the false alarm probability $P_f$ will decrease accordingly, which further improves the EE of the studied CSS scheme.

From (7), we know that $\varepsilon_s^*(\omega)$ has to fulfill the condition $\varepsilon_s^*(\omega) > \sigma_u^2$ in order to make $P_f < 0.5$, which should be the case for most CR scenarios. To this end, we get $\tau_s > \tau_s^{min}$ by considering (18), where

$$\tau_s^{min} = \frac{M\alpha_{arit}^2\sigma_u^4(2\gamma+1)}{2W\left[\left(\frac{\gamma M\alpha_{arit}\sigma_u^2}{-Q^{-1}(\omega)}\right)^2 - \frac{\Omega_1(M-1+2\sigma_u^2)+\sigma_u^4}{L}\right]}. \qquad (20)$$

Further, in order to guarantee $\tau_s^{min} \geq 0$, we require $L \geq L_{min}$, where

$$L_{min} \tag{21}$$
$$= \max\left(\left\lceil \frac{\left(\Omega_1(M-1+2\sigma_u^2)+\sigma_u^4\right)\left(-Q^{-1}(\omega)\right)^2}{\gamma^2 M^2 \alpha_{arit}^2 \sigma_u^4} \right\rceil, L_{lower}\right).$$

Plugging (18) into problem (17), we then achieve its equivalent form under the condition $\tau_{min} \leq T-2\tau$

$$\max\ \xi(\tau_s, L) := \xi(\tau_s, \varepsilon_s, L)|_{\varepsilon_s=\varepsilon_s^*(\omega)} \tag{22a}$$
$$s.t.\ \tau_{min} < \tau_s \leq T-2\tau, \tag{22b}$$
$$L_{min} \leq L \leq L_{max}, \tag{22c}$$

where $\xi(\tau_s, L) = \frac{(T-2\tau-\tau_s)C_0 \Pr(\mathscr{H}_0)\left(1-P_f(\tau_s, L; \varepsilon_s^*(\omega))\right)/T}{M(E_s\tau_s+LE_t\nu)+E_t \Pr(\mathscr{H}_0)(T-2\tau-\tau_s)(1-P_f(\tau_s, L; \varepsilon_s^*(\omega)))}$.

Therefore, the feasibility of problem (22) is guaranteed.

### B. Iterative Solution Algorithm

Instead of directly solving the two-variable optimization problem (22), we propose the ISA that decouples problem (22) into two single-variable suboptimal problems and solve them iteratively until convergence.

*1) Sensing time optimization:* For a given $\tilde{L}$, the first suboptimization problem of (22) is given as

$$\max\ \xi(\tau_s) := \xi(\tau_s, L, \varepsilon_s)|_{L=\tilde{L}, \varepsilon_s=\varepsilon_s^*(\omega)} \tag{23a}$$
$$s.t.\ \tau_{min} < \tau_s \leq T-2\tau. \tag{23b}$$

*Lemma 2:* $F(\tau_s) := F(\tau_s, \varepsilon_s, L)|_{L=\tilde{L}, \varepsilon_s=\varepsilon_s^*(\omega)}$ is strictly concave in $\tau_s$ when $\tau_s$ falls in the domain defined by (23b).

The proof of Lemma 2 will be given in Appendix A.

Similarly, we can prove that $C(\tau_s) := C(\tau_s, \varepsilon_s, L)|_{L=\tilde{L}, \varepsilon_s=\varepsilon_s^*(\omega)}$ is also strictly concave in $\tau_s$ when $\tau_{min} < \tau_s \leq T-2\tau$. We transform problem (23) into an equivalent form

$$\min_{\tau_{min} < \tau_s \leq T-2\tau}\ \phi(\tau_s) = \frac{-F(\tau_s)}{C(\tau_s)}. \tag{24}$$

*Definition 1:* [37] A function $Q: \mathbf{R}^n \mapsto \mathbf{R}$ is called quasi-convex if its domain and all its sublevel sets $S_\alpha = \{x \in \mathbf{dom}Q | Q(x) \leq \alpha\}$, for all $\alpha \in \mathbf{R}$, are convex.

According to Definition 1, we get the sublevel set of $\phi(\tau_s)$

$$S_\alpha = \{\tau_s | \tau_{min} < \tau_s \leq T-2\tau, f_\alpha(\tau_s) \leq 0\}, \tag{25}$$

where $f_\alpha(\tau_s) = -F(\tau_s) - \alpha C(\tau_s)$.

Taking the second derivative of $f_\alpha(\tau_s)$ with respect to $\tau_s$, we get

$$f''_\alpha(\tau_s) = -\Pr(\mathscr{H}_0)\left(\frac{C_0}{T}+\alpha E_t\right)\left(2P'_f(\tau_s; \tilde{L}, \varepsilon_s^*)\right.$$
$$\left. -(T-2\tau-\tau_s)P''_f(\tau_s; \tilde{L}, \varepsilon_s^*)\right).$$

According to the proof of Lemma 2, we conclude that $f''_\alpha(\tau_s) > 0$ when $\frac{C_0}{T}+\alpha E_t \geq 0$ . Therefore, $\phi(\tau_s)$ is quasi-convex in $\tau_s$ and as a result, problem (24) is a quasi-convex optimization problem with respect to $\tau_s$ for $\alpha \geq l$ ($l = \frac{-C_0}{TE_t}$).

We propose a simple bisection-based algorithm to problem (24) by solving a series of convex feasibility problems. Let $\phi^*$ denote the optimal value of the quasi-convex problem (24). If the convex feasibility problem

$$\text{find}\ \ \tau_s \tag{26a}$$
$$s.t.\ f_\alpha(\tau_s) \leq 0, \tag{26b}$$
$$\tau_{min} < \tau_s \leq T-2\tau, \tag{26c}$$

is feasible, then we have $\phi^* \leq \alpha$. Conversely, if the problem (26) is infeasible, then we can conclude $\phi^* > \alpha$. Thus, we can check whether the optimal value of a quasi-convex problem is less than or more than a given value $\alpha$ by solving the convex feasibility problem (26).

When $\alpha \geq 0$, $f_\alpha(\tau_s) \leq 0$ always holds. Thus, we conclude that the interval $[l,\ u]$ with $u = 0$ contains the optimal value $\phi^*$. We then solve the convex feasibility problem at its midpoint $\alpha = \frac{l+u}{2}$, to determine whether $\phi^*$ is in the lower or upper half of the interval, and update the interval accordingly. This produces a new interval, which also contains $\phi^*$, but has half the width of the initial interval. This is repeated until the width of the interval is small enough. The above procedure is summarized in Algorithm 1.

The interval $[l,\ u]$ is guaranteed to contain $\phi^*$, i.e., we have $l \leq \phi^* \leq u$ at each step. In each iteration, the interval is bisected, so the length of the interval after $k$ iterations is $2^{-k}(u-l)$, where $u-l$ is the length of the initial interval. It follows that exactly $\lceil \log_2((u-l)/\varepsilon) \rceil$ iterations are required before the algorithm terminates. Each step involves solving the convex feasibility problem (26). Efficient solution methods, such as interior-point methods [37], could be then employed to solve problem (26) in polynomial time.

**Algorithm 1** Bisection-based solution algorithm

**Input**: $l$, $u$, $L_{lower}$, $L_{max}$, $T$, $\tau$, $C_0$, $\omega$, $\gamma$, $M$, $E_t$, $E_s$, $\nu$, $W$, $\sigma_u^2$, $\alpha_{arit}$, $\Pr(\mathscr{H}_0)$ and $\Pr(\mathscr{H}_1)$ and tolerance $\varepsilon > 0$.
**Initialization**: $m \leftarrow 0$, $l(m) \leftarrow \frac{-C_0}{TE_t}$, $u(m) \leftarrow 0$, $\tau_s(m) \leftarrow 0$.
**repeat**
  $\alpha(m) \leftarrow (l(m)+u(m))/2$.
  Solve the convex feasibility problem (26) with $\alpha(m)$.
  **If** problem (26) with $\alpha(m)$ is feasible
    $u(m+1) \leftarrow \alpha(m)$;
    $\tau_s(m+1) \leftarrow x$. % save the feasible solution
  **else**
    $l(m+1) \leftarrow \alpha(m)$.
  **EndIf**
  $m \leftarrow m+1$.
**until** $u(m)-l(m) \leq \varepsilon$.
**Output**: $\check{\tau}_s = \tau_s(m)$.

*2) Sequence length optimization:* For a given $\tilde{\tau}_s$, the second suboptimization problem of (22) is given as

$$\max\ \xi(L) := \xi(\tau_s, L, \varepsilon_s)|_{\tau_s=\tilde{\tau}_s, \varepsilon_s=\varepsilon_s^*(\omega)} \tag{27a}$$
$$s.t.\ L_{min} \leq L \leq L_{max}. \tag{27b}$$

No closed-form solution for $L$ is available for problem (27), and an exhaustive search over all feasible $L$ is required. Due to the integer nature of $L$, it is not computationally expensive to perform exhaustive search for an optimal $L$. Note that the

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uniqueness of the optimal $L$ is not guaranteed. In the case of multiple optimal solutions, the one with the smallest value is preferable, since energy could be saved by shrinking the length of the sequence.

*3) Global algorithm and convergence analysis:* Combining the steps for solving the two suboptimization problems of problem (22), we summarize the proposed ISA in Algorithm 2.

**Algorithm 2** Iterative Solution Algorithm (ISA)

1: **Input**: $L_{lower}$, $L_{max}$, $T$, $\tau$, $C_0$, $\omega$, $\gamma$, $M$, $E_t$, $E_s$, $\nu$, $W$, $\sigma_u^2$, $\alpha_{arit}$, $\Pr(\mathscr{H}_0)$ and $\Pr(\mathscr{H}_1)$.
2: **Initialization**: $n \leftarrow 0$, $L(0) \leftarrow L_{max}$.
3: **repeat**
4: Update $\tau_{min}(n)$ and $L_{min}(n)$ according to (20) and (21), respectively.
5: Given $L(n)$, find $\check{\tau}_s(n)$ that solves problem (23) by Algorithm 1.
6: $\tau_s(n+1) \leftarrow \check{\tau}_s(n)$.
7: Given $\tau_s(n+1)$, find $\check{L}(n)$ using exhaustive search, i.e.,

$$\check{L}(n) = \arg \max_{s.t.\ (27b)} \xi(L).$$

8: $L(n+1) \leftarrow \check{L}(n)$.
9: $n \leftarrow n+1$.
10: **until** $\xi(\tau_s(n), L(n)) \leq \xi(\tau_s(n-1), L(n-1))$.
11: **Output**: $\hat{\tau}_s = \tau_s(n)$, $\hat{L} = L(n)$.

Next, we analyze the convergence and the optimality of the proposed ISA. Let $\xi^*$ denote the optimum of problem (22). Let $(\tau_s(n), L(n))$ denote the value of variables $(\tau_s, L)$ after the $n$-th iteration in ISA.

*Theorem 1:* Given an initial feasible $L(0)$ fulfilling constraint (27b), $\{\xi(\tau_s(n), L(n))\}$ in Algorithm 2 converges to a steady value $\hat{\xi} \leq \xi^*$.

*Proof:* From Algorithm 2, we can conclude that the objective function of problem (22), $\xi(\tau_{\mathbf{s}}, L)$, is nondecreasing at each iteration, i.e., $\forall\ n$,

$$\xi(\tau_s(n), L(n)) \leq \xi(\tau_s(n+1), L(n)) \leq \xi(\tau_s(n+1), L(n+1)).$$

It is also obvious that the feasible domain of problem (22) is closed and $\xi(\tau_s, L)$ is continuous on the feasible domain, which implies that $\xi(\tau_s, L)$ is bounded from above. This together with the monotonicity proves the convergence of $\xi(\tau_s(n), L(n))$. This completes the proof of Theorem 1. ■

Let $(\hat{\tau}_s, \hat{L})$ denote a solution to $\hat{\xi} = \xi(\tau_s, L)$. From the proof of Theorem 1, we find that the convergence point $(\hat{\tau}_s, \hat{L})$ is with the following property: at $(\hat{\tau}_s, \hat{L})$, $\xi(\hat{\tau}_s, \hat{L}) \geq \xi(\tau_s, \hat{L})$ for all $\tau_s$ and $\xi(\hat{\tau}_s, \hat{L}) \geq \xi(\hat{\tau}_s, L)$ for all $L$. In other words, at $\hat{\tau}_s$, $\xi(\hat{\tau}_s, \hat{L})$ is the largest across the dimension of $\tau_s$, and at $\hat{L}$, $\xi(\hat{\tau}_s, \hat{L})$ is the largest across the dimension of $L$. Although we cannot rigorously prove the global optimality of the ISA, we have found from the simulations in Section VI that the ISA is insensitive to the initial value of $L(0)$ and always converges to the same maximum point, i.e., $\hat{\xi} = \xi^*$.

TABLE I
PARAMETER VALUES USED IN THE SIMULATION

| Parameter | Value |
|---|---|
| the number of CSs $M$ | $[10, 20]$ |
| the lower bound of $L$, $L_{lower}$ | 200 |
| the upper bound of $L$, $L_{max}$ | 625 |
| the transmit power $E_t$ | 3 Watt |
| the sensing power $E_s$ | 0.1 Watt |
| the symbol duration $\nu$ | 16 $\mu$s |
| the average received SNR at each CS $\gamma$ | $[-16,\ 0]$ dB |
| the lower bound on the detection probability $\omega$ | 0.9 |
| the occurrence probability of $\mathscr{H}_1$ $\Pr(\mathscr{H}_1)$ | 0.2 |
| the occurrence probability of $\mathscr{H}_0$ $\Pr(\mathscr{H}_0)$ | 0.8 |
| the bandwidth of the licensed band $W$ | 3 MHz |
| the sampling frequency $f_s$ | 6 MHz |
| the CSN throughput when PUs are inactive $C_0$ | 6.6582 bits/sec/Hz |
| the CSN throughput when PUs are active $C_1$ | 6.6137 bits/sec/Hz |
| the length of one time frame $T$ | 300 ms |
| the variance of noise $\sigma_u^2$ | 1 |
| the coefficient of transmit power coding $\alpha_{arit}$ | 10 |
| the length of one mini-slot $\tau$ | 10 ms |

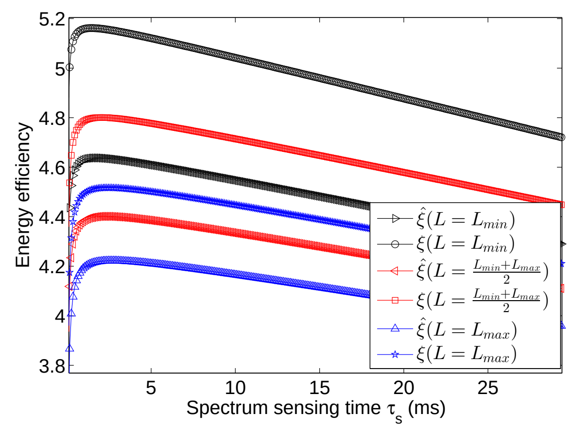


Fig. 2. EE for the CSN: $\gamma = -16$dB and $M = 10$ (Fixed $L$)

## VI. PERFORMANCE EVALUATION

This section presents the simulation results to verify the effectiveness of this work. All simulated parameters are summarized in Table I, representing values describing typical CR and CSN scenarios [3] [6] [20]. First, we are interested in the exact EE of the CoMAC-based CSS scheme, $\hat{\xi}(\tau_s, \varepsilon_s, L)$, which is defined as

$$\hat{\xi}(\tau_s, \varepsilon_s, L) = \frac{\hat{F}(\tau_s, \varepsilon_s, L)}{\hat{C}(\tau_s, \varepsilon_s, L)}, \tag{28}$$

where $\hat{C}(\tau_s, \varepsilon_s, L)$ and $\hat{F}(\tau_s, \varepsilon_s, L)$ are defined in (12) and (14), respectively. Fig. 2 shows that both $\xi(\tau_s, \varepsilon_s, L)$ of (16) and $\hat{\xi}(\tau_s, \varepsilon_s, L)$ of (28) achieve their respective maximums at the same spectrum sensing times of about $2.5ms$ for different values of $(\varepsilon_s,\ L)$ (i.e., $\varepsilon_s = \varepsilon_s^*(\tau_s, L; \omega)$ and $L = \{L_{min}, \frac{(L_{min}+L_{max})}{2}, L_{max}\}$. Fig. 3 shows that both $\xi(\tau_s, \varepsilon_s, L)$ and $\hat{\xi}(\tau_s, \varepsilon_s, L)$ decrease with the increase of $L$ and thus achieve their maximum at the same symbol sequence length of $L_{min} = 294$ for different values of $(\varepsilon_s, \tau_s)$ (i.e., $\varepsilon_s = \varepsilon_s^*(\tau_s, L; \omega)$ and $\tau_s = \{5ms, 50ms, 100ms\}$), which again demonstrates the approximation operation to $\hat{\xi}(\tau_s, \varepsilon_s, L)$ does not harm the optimality of $\{\tau_s, \varepsilon_s, L\}$.

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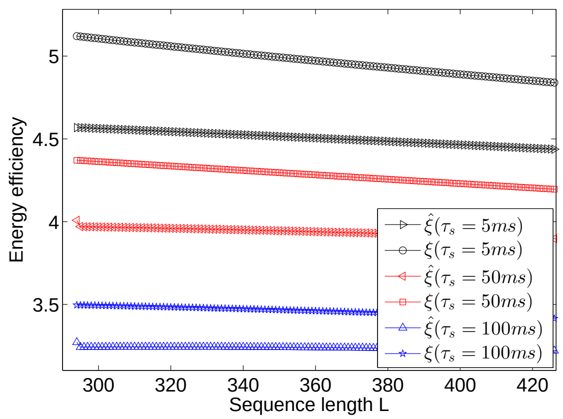


Fig. 3. EE for the CSN: $\gamma = -16$dB and $M = 10$ (Fixed $\tau_s$)

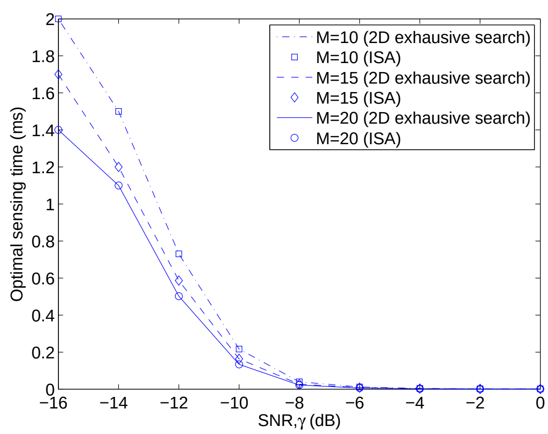


Fig. 4. Optimal sensing time that maximizes the EE.

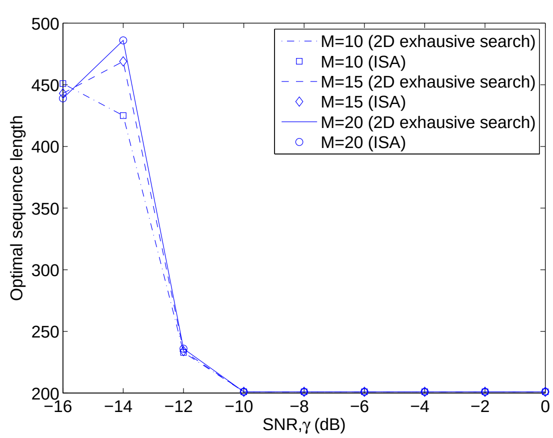


Fig. 5. Optimal symbol sequence that maximizes the EE.

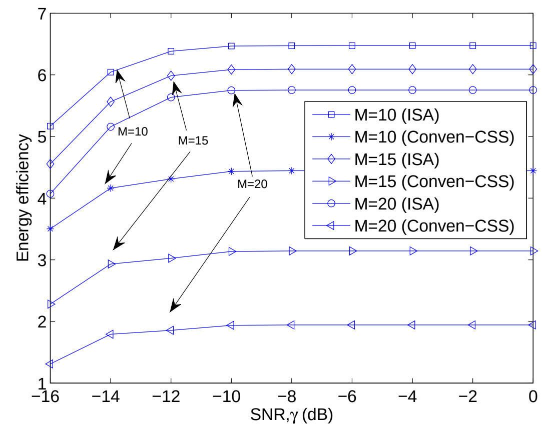


Fig. 6. Maximum EE comparison for various $\gamma$s.

Fig. 4 and Fig. 5 show the optimal $\tau_s$ and $L$ at different values of $\gamma$, respectively. The problem (22) is solved by using the ISA, and the obtained solutions are compared with those determined by a 2-dimensional (2D) exhaustive search over $\tau_s$ and $L$. One important observation in Fig. 4 is that the optimal sensing time monotonically decreases in the SNR $\gamma$ and the number of CSs $M$. This stems from the fact that larger $\gamma$ and $M$ need fewer signal examples to maintain the same sensing accuracy than smaller $\gamma$ and $M$. Unlike Fig. 4, Fig. 5 shows that the optimal sequence length is not monotonic in $\gamma$ and $M$, which highlights the necessity of the extensive search in problem (27). It can be observed from Figs. 4 and 5 that the proposed ISA solutions coincide with the global optimal values for $\tau_s$ and $L$ in all cases. Because of this consistency, in the following simulations, we will only consider the proposed results.

Fig. 6 compares the maximum EE of this work with that of conventional CSS schemes (denoted by ”Conven-CSS”) [20] [25] [27] [29]-[31] when $\gamma$ and $M$ vary, respectively. In conventional CSS schemes, the local statistic of each CS has to be sent to the fusion center in different time slots, as a result of which the reporting delay during the reporting phase of conventional CSS grows linearly with $M$. The “$K$-out-of-$M$” fusion (the same $P_f$ is assumed) is adopted by the fusion center. For notational convenience, the maximum EE of conventional CSS schemes is denoted by $\xi_{con}$, which is given by

$$\xi_{con} = \frac{(T-(M+1)\tau-\tau_s)C_0\Pr(\mathscr{H}_0)(1-P_f)/T}{M(E_s\tau_s+E_t\tau)+\Pr(\mathscr{H}_0)(1-P_f)(T-(M+1)\tau-\tau_s)E_t}.$$

For fair comparison, all the parameters in $\xi_{con}$ are selected from Table 1. It is clearly shown in Fig. 6 that the EE of ISA is much higher than that of conventional CSS schemes, regardless of $\gamma$ and $M$. The maximum performance gain (i.e., $\hat{\xi}/\xi_{con}$) reaches up to 3.1070 which occurs when $\gamma = -16$ dB and $M = 20$. Finally, we find that the steady state of EE arrives when $\gamma$=-8dB in Fig. 6, which is consistent with the results in Fig. 4 and Fig. 5 since the steady states of both optimal $\tau_s$ and $L$ also arrive when $\gamma$=-8dB.

Fig. 7 presents the comparison result between the maximum

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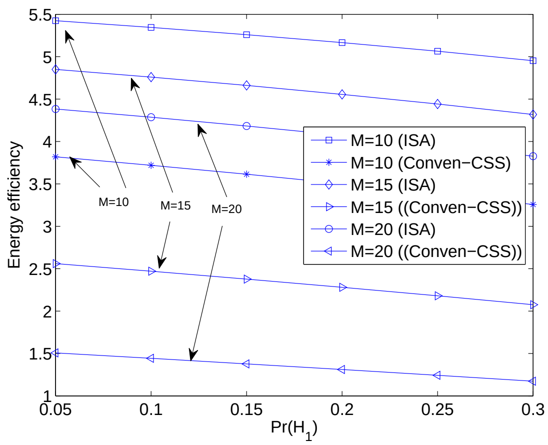


Fig. 7. Maximum EE comparison for various $\Pr(\mathscr{H}_1)$s.

EE of this work with that of conventional CSS schemes under different $\Pr(\mathscr{H}_1)$s. Without loss of generality, we fix $\gamma = -16$dB and vary $\Pr(\mathscr{H}_1)$ from 0.05 to 0.3. Similar to Fig. 6, the EE of ISA is again much higher than that of conventional CSS schemes in Fig. 7, regardless of $\Pr(\mathscr{H}_1)$ and $M$. It is also obvious in Fig. 7 that the EEs of all the compared CSS schemes decrease with the increase of $\Pr(\mathscr{H}_1)$, which implies the fact that the loss in throughput performance due to the increasing occurrence of PUs dominates the energy saving in the transmission phase of CSS schemes.

## VII. Conclusion

This paper has formulated a novel EE-maximization problem for the CoMAC-based soft decision CSS scheme in CSNs. In order to solve the EE-maximization problem, we first have found the optimal expression for the detection threshold and then proposed an ISA to find an efficient pair of sensing time and the length of the modulated symbol sequence. The ISA decouples the EE-maximization problem into two subproblems (i.e., the sensing time optimization and the sequence length optimization) and solves them iteratively until convergence. For a given length of symbol sequence, we have proved the quasi-convexity of the sensing time optimization problem and proposed a bisection-based solution algorithm to solve it. Further, provided the newly computed sensing time, we have found the optimal length of symbol sequence to the sequence length optimization problem via exhaustive search.

Extensive simulations have demonstrated the effectiveness of this work despite of the heuristic decomposition method by the proposed ISA. By comparing this work with conventional CSS schemes, we have shown a large performance gain in EE due to this work.

## Appendix A
## Proof of Lemma 2

*Proof:* First, we take the second derivative of $F(\tau_s)$ with respect to $\tau_s$

$$F^{''}(\tau_s) = \frac{C_0 \Pr(\mathscr{H}_0)(2P_f^{'} - (T - 2\tau - \tau_s)P_f^{''})}{T}. \tag{29}$$

It is evident from (29) that the concavity of $F(\tau_s)$ can be declared if $P_f(\tau_s; \tilde{L}, \varepsilon_s^*)$ is monotonic decreasing and convex in $\tau_s$.

Then, taking derivative of $P_f(\tau_s; \tilde{L}, \varepsilon_s^*)$ with respect to $\tau_s$ yields

$$P_f^{'}(\tau_s; \tilde{L}, \varepsilon_s^*) = -\frac{1}{\sqrt{2\pi}} \exp\left(-\Theta^2(\tau_s)\right) \Theta^{'}(\tau_s) \tag{30}$$

with $\Theta(\tau_s) = \frac{Q^{-1}(\omega)\sqrt{A + \frac{B}{\tau_s}} + C}{\sqrt{D + \frac{E}{\tau_s}}}$, where $A = L\Omega_1(M - 1 + 2\sigma_u^2) + L\sigma_u^4$, $B = \frac{L^2 M \sigma_u^4 \alpha_{arit}^2 (2\gamma + 1)}{2W}$, $C = LM\alpha_{arit}\gamma\sigma_u^2$, $D = L\Omega_0(M - 1 + 2\sigma_u^2)$ and $E = \frac{L^2 M \sigma_u^4 \alpha_{arit}^2}{2W}$.

Further, skipping the tedious deduction we expand $\Theta^{'}(\tau_s)$ as follows

$$\Theta^{'}(\tau_s) = \underbrace{\frac{Q^{-1}(\omega)(AE - BD)}{2(A\tau_s + B)^{\frac{3}{2}}\sqrt{D\tau_s + E}}}_{\Phi_1(\tau_s)} + \underbrace{\frac{EC}{2\tau_s^2\left(D + \frac{E}{\tau_s}\right)^{\frac{3}{2}}}}_{\Phi_2(\tau_s)}. \tag{31}$$

It is trivial to verify that $AE - BD > 0$, which together with $Q^{-1}(\omega) < 0$ (as $\omega$ is close to 1) proves that $\Theta^{'}(\tau_s) > 0$. Combining (30) and (31), we conclude that $P_f^{'}(\tau_s; \tilde{L}, \varepsilon_s^*) < 0$, i.e., $P_f(\tau_s; \tilde{L}, \varepsilon_s^*)$ is monotonic decreasing in $\tau_s$.

When $\varepsilon_s^*(\omega) > \sigma_u^2$ ($\tau_s > \tau_{min}$), $Q^{-1}(\omega)\sqrt{A + \frac{B}{\tau_s}} + C \geq 0$ holds and we thus have $\Theta(\tau_s) > 0$. As both $\Phi_1(\tau_s)$ and $\Phi_2(\tau_s)$ are monotonic decreasing in $\tau_s$, $\Theta^{'}(\tau_s)$ is also monotonic decreasing in $\tau_s$. This, together with $\Theta(\tau_s) \geq 0$, implies that $P_f^{'}(\tau_s; \tilde{L}, \varepsilon_s^*)$ is increasing in $\tau_s$, i.e., $P_f^{''}(\tau_s; \tilde{L}, \varepsilon_s^*) > 0$. So far, we have proved that $F^{''}(\tau_s)$ in (29) is negative, which implies the strict concavity of $F(\tau_s)$. ■

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