Energy-Efficient Cooperative Spectrum Sensing in Cognitive Satellite Terrestrial Networks

JING HU [1], **GUANGXIA LI**[1], **DONGMING BIAN**[1], **SHENGCHAO SHI** [2], **RUIXING GE**[1], **AND LIANG GOU**[3]

[1]College of Communications Engineering, Army Engineering University of PLA, Nanjing 210000, China
[2]Beijing Institute of Information Technology, Beijing 100094, China
[3]Nanjing Smart Constellation Information Technology Company Ltd., Nanjing 210000, China

Corresponding author: Shengchao Shi (shishengchao88@gmail.com)

ABSTRACT Having the ability to provide seamless coverage and alleviate the frequency scarcity, the cognitive satellite terrestrial network becomes a promising candidate for future communication networks. In the cognitive network, spectrum sensing plays an important role in detecting the channel state for opportunistic utilization, where cooperative spectrum sensing is employed to improve the sensing performance. Additionally, it is critical for battery-powered satellite mobile terminals to diminish energy consumption costs. In this regard, this paper proposes a novel sensing-based cognitive satellite terrestrial network (SCSTN), which integrates the cognitive satellite terrestrial network with the distributed cooperative spectrum sensing network. Specifically, we focus on energy-efficient cooperative sensing in the SCSTN, which maximizes the energy efficiency (EE) of the cognitive satellite network by a tradeoff between the average throughput and the average energy consumption. In the SCSTN, the energy detection threshold of the sensing node and the rule threshold of fusion affect the average throughput and the average energy consumption. Hence, the objective of this paper is to identify the energy detection threshold of the sensing node and the rule threshold of fusion to achieve the maximum EE. We first study the EE formulation of the rule threshold of fusion when the energy detection threshold of the sensing node is given, and transform the ratio-type objective function of EE into a parametric formulation. Subsequently, by exploring the relationship between the two formulations and making use of the monotonicity of the parametric formulation, an algorithm to obtain the optimal rule threshold of fusion for the original problem is developed. Furthermore, we study the optimal formulation of the energy sensing threshold of the sensing node and discuss the effect of the sensing duration and the number of distributed cooperative terminals on the EE. Lastly, the performance of the proposed method is evaluated through numerical simulation results.

INDEX TERMS Cognitive satellite terrestrial network, distributed spectrum sensing, satellite communication, energy efficiency, detection probability, false alarm probability.

I. INTRODUCTION

Cognitive radio (CR) has attracted attention for improving the spectrum efficiency in recent years [1]–[7]. In the CR network, the secondary user (SU) either coexists with the primary user (PU) with the strict power constraints or opportunistically accesses the spectrum allocated to the PU when the PU is idle [8]–[10].

Due to the obvious superiority in high data rate services and seamless coverage, the satellite terrestrial network plays

The associate editor coordinating the review of this manuscript and approving it for publication was Hayder Al-Hraishawi .

an important role in future space communication systems [11]–[13]. However, the issue of spectrum scarcity has restricted the development of them. To alleviate pressure on limited spectrum resource, CR has been introduced for the satellite terrestrial network as a promising technology [14]–[20]. In [17], the outage probability of the cognitive network with interference temperature constraint is studied, where the satellite communication network acts as the PU while the terrestrial mobile network serves as the SU. Considering the Quality of Service (QoS) of the primary terrestrial network, paper [18] introduces a new power allocation method to optimize the capacity of the PU while guaranteeing

the outage probability of the secondary satellite network. By employing the interference constraint at the terrestrial user, the expression for the cognitive satellite uplink capacity is derived in [19] where the channel statistical properties, propagation losses, and antenna patterns are considered. However, the above researches aim to achieve spectrum sharing by various interference constraints in the cognitive satellite terrestrial network, and the high capacity performance of the satellite communication network is not considered.

According to the data provided in [21], many precious spectrums allocated to terrestrial users are idle. Therefore, if the idle state of the primary terrestrial user can be effectively sensed, the cognitive satellite network can use the same spectrum according to its interests to achieve higher capacity. Hence, accurate sensing the state of the primary terrestrial network is the premise of this approach. Up to now, sensing-based cognitive radio system has attracted many researchers [22]–[25]. In [22], a hybrid approach that combines the spectrum sensing approach with the underlay approach is introduced. In [23], the average achievable throughput under a single high target detection probability constraint, and the ergodic throughput with the average transmit and the target detection probability are discussed. In [25], the paper examines the sensing throughput tradeoff of a cognitive radio network, which is based on the spectrum sensing algorithm where the noise variance uncertainty is considered. However, these above works consider that only one sensing terminal is in the network. To improve the sensing accuracy, a distributed cooperative spectrum sensing method is proposed [26]–[30], where the fusion center assembles the sensing information from the distributed sensing nodes to make a final decision for the cognitive network. In [26], the paper study the optimality of cooperative spectrum sensing, which aims to optimize the detection performance in an efficient method. To improve the throughput of secondary users by reducing the reporting duration, the paper [29] introduces a cooperative spectrum sensing approach with two-stage reporting. In [30], the paper proposes a composite cooperation sensing scheme in which multiple secondary users simultaneously perform spectrum sensing and data transmission in two different parts of the primary user spectrum. However, distributed cooperative sensing improves the sensing performance, while requires more energy consumption of sensing and reporting. In the wide application of satellite communications, such as the Internet of Things (IoTs), disaster response, emergency communications, etc. [31]–[34], the battery power affected the service life and performance of the portable satellite terminal. Besides, in [35], [36], papers indicate information and communication technologies have brought about 10% of the global energy consumption and 2% of the greenhouse gas. In this context, reducing energy consumption is a new challenge for the satellite communication network [37]–[39].

In this paper, we define EE as the ratio of the transmitted bits over the average energy consumption in the SCSTN. Since the rule threshold of fusion and the energy detection threshold of the sensing node determine the cooperative sensing performance, and effect on the average throughput and the transmission energy, the objective of this paper is to optimize these parameters to maximize the EE of the SCSTN. The contributions of the paper can be summarized as follows. Firstly, a network architecture that integrates the distributed cooperative sensing network and the cognitive satellite terrestrial network is presented. Secondly, we derive the EE formulation under the cooperative spectrum sensing frame structure in the SCSTN. This formulation is related to the rule threshold of fusion, the energy detection threshold of the sensing node, the sensing duration, and the number of distributed cooperative terminals. Subsequently, to identify the optimal rule threshold of fusion, we transform the original EE formulation to the parametric formulation. Then, by exploring the relationship between these two formulations and making use of the monotonicity of the parametric formulation, an algorithm is developed to obtain the optimal rule threshold of fusion. Furthermore, the optimal formulation of the energy sensing threshold at the sensing node is studied and we discuss the effect of the sensing duration and the number of distributed cooperative terminals on the EE.

The following section of this paper is structured as follows: In Section II, the SCSTN architecture and the cooperative spectrum sensing frame structure are presented. In Section III, the EE expression of the SCSTN is introduced. In Section IV, the solutions of maximizing the EE by the rule threshold of fusion and the energy detection threshold of the sensing node are formulated, respectively. Numerical simulation results are presented in Section V and we conclude the paper in Section VI.

II. SYSTEM MODEL
A. SYSTEM MODEL
Fig. 1 depicts the integrated sensing based cognitive satellite terrestrial network architecture, which is composed of the terrestrial network, the cognitive satellite network, and the distributed cooperative sensing network. More details are presented as follows.
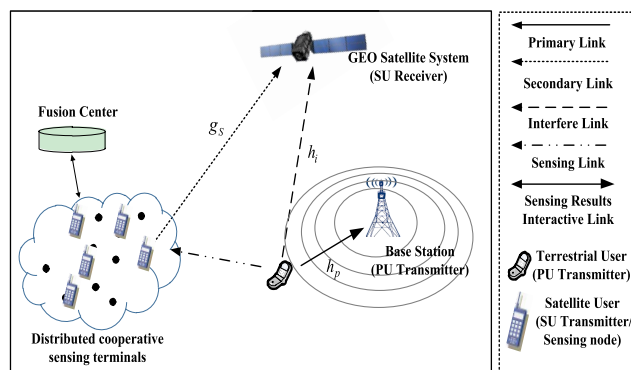

FIGURE 1. Cognitive satellite terrestrial network based on distributed cooperative sensing.

Terrestrial network: The terrestrial network acts as PU, and the link between the mobile terminal and the base station, which is assigned to PU, is called a primary link. And h_p denotes the gain of the primary link.

Cognitive satellite network: The cognitive satellite network plays the role of SU in the architecture. The satellite terminals, which act as the distributed cooperative sensing nodes, opportunistic access the spectrum that belongs to the terrestrial network according to the fusion decision. Herein, g_s denotes the gain of the cognitive uplink. Additionally, according to the cognitive radio system model, when SU and PU are busy simultaneously, the PU will interfere with the SU, therefore h_i represents the gain of the interference link [40], [41].

Distributed cooperative sensing network: In the sensing network, the distributed satellite portable terminals act as not only the SUs but also the cooperative sensing nodes which can sense the terrestrial network state and report the sensing results to the fusion center through the forward channel. The fusion center combined the multiple terminals sensing results and issue a final decision through the backward broadcast channel. If the fusion decision shows the terrestrial network state is idle, the satellite terminal can access the spectrum to communicate. Otherwise, the satellite terminal cannot utility the spectrum. Herein, the dot-dash line denotes the sensing link which is between the terrestrial mobile terminal and the distributed satellite terminal.

In this paper, the system is assumed perfectly synchronized, and the time is divided into frames whose duration is T as shown in Fig. 2. Each frame consists of three parts: the sensing duration τ, the reporting duration $M\xi$, and the transmission duration $T - \tau - M\xi$, where M denotes the number of the satellite terminals and ξ represents the reporting duration of a single terminal. During the sensing duration, satellite terminals, which play the role of the sensing nodes in the cooperative sensing network, can detect the PU state. Additionally, in the reporting duration, the satellite terminals report the sensing results to the fusion center in turn. Finally, in the data transmission duration, if the fusion center issues the state of PU is idle, the satellite terminal can access the spectrum based on its benefit to achieve high capacity.
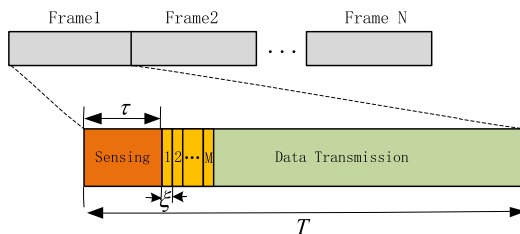

FIGURE 2. Frame structure of the cooperative periodic spectrum sensing.

B. DISTRIBUTED SPECTRUM SENSING

The spectrum sensing is a technique for determining the idle/busy state of the PU, which is considered as a binary

hypothesis problem. Therefore, hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$ is denoted the idle/busy state of PU, respectively. When energy detector is used at each satellite terminal to detect the PU state, the detection probability p_d and the false alarm probability p_f can be calculated as [22]

$$p_d\left(\varepsilon, \tau\right) = Q\left(\left(\frac{\varepsilon}{\sigma_n^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma + 1}}\right) \quad (1)$$

and

$$p_f\left(\varepsilon, \tau\right) = Q\left(\left(\frac{\varepsilon}{\sigma_n^2} - 1\right)\sqrt{\tau f_s}\right) \quad (2)$$

where ε is the detection threshold, τ is the sensing duration, f_s denotes the sampling frequency, γ refers the SNR of received signal at satellite terminal, σ_n^2 is the power of the noise and satisfies $\sigma_n^2 = 1$, and $Q\left(\cdot\right)$ denotes the complementary distribution function of the standard Gaussian i.e. $Q\left(x\right) = \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{t^2}{2}\right)dt$. Without loss of generality, it is assumed the distances between these satellite terminals are shorter than that between the satellite terminals and the terrestrial network. Hence, the signals that the satellite terminals receive have identical path loss. In this context, p_d and p_f of each satellite terminal is assumed to be equal.

In the fusion center, the k-out-of-M fusion rule is used to make the final decision, where k is the rule threshold of fusion, M denotes the number of distributed cooperative satellite terminals and $0 < k \leq M$ [22]. Specifically, if more than k sensing results of satellite terminal say that there is a terrestrial terminal, and the fusion decision declares the terrestrial network state is busy; otherwise, the terrestrial network state is idle. The detection probabilities Q_d and the false alarm probabilities Q_f at the fusion center are given by

$$Q_d\left(\varepsilon, \tau, k, M\right) = \sum_{m=k}^{M}\binom{M}{m}p_d(\varepsilon, \tau)^m(1 - p_d\left(\varepsilon, \tau\right))^{M-m}$$

$$(3)$$

and

$$Q_f\left(\varepsilon, \tau, k, M\right) = \sum_{m=k}^{M}\binom{M}{m}p_f(\varepsilon, \tau)^m\left(1 - p_f\left(\varepsilon, \tau\right)\right)^{M-m}$$

$$(4)$$

where $\binom{M}{m} = \frac{M!}{m!(M-m)!}$.

III. PROBLEM FORMULATION
A. AVERAGE THROUGHPUT OF NETWORK
Considering the real state of the terrestrial network and the cooperative sensing results, there are two possible scenarios where the satellite terminal can access the spectrum.

Scenario 1: when the terrestrial network is idle and no false alarm happens, the throughput of the satellite network is $C_0 = \log_2\left(1 + \frac{g_s p_t}{N_0}\right)$, where p_t denotes the transmit power of the satellite terminal and N_0 presents the noise power.

Scenario 2: when the terrestrial network is active and a miss detection happens, the throughput of the satellite network is $C_1 = \log_2\left(1 + \frac{g_s p_t}{N_0 + h_i p_i}\right)$, where p_i denotes the transmit power of the terrestrial terminal.

In this context, the average throughput of the satellite network can be written as

$$R(\varepsilon, \tau, k, M) = (T - \tau - M\xi) \cdot \left(\mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right)C_0 \right.$$
$$\left. + \mathcal{P}(\mathcal{H}_1)\left(1 - Q_d\right)C_1\right) \quad (5)$$

where $\mathcal{P}(\mathcal{H}_0)$ and $\mathcal{P}(\mathcal{H}_1)$ represent the probability of busy and idle state of the terrestrial network, respectively, and $\mathcal{P}(\mathcal{H}_1) + \mathcal{P}(\mathcal{H}_0) = 1$. In practice, Q_d is close to but less than 1, especially for low SNR. For example, in IEEE 802.22 WRAN, the target detection probability is 0.9 for the SNR is -20dB. Additionally, without loss of generality we assume that the activity probability $\mathcal{P}(\mathcal{H}_1)$ is small, thus it make sense to explore the cognitive radio technology for the secondary user to reuse the frequency band [22], [42]. Hence, the average throughput of the satellite network can be written as

$$\tilde{R}(\varepsilon, \tau, k, M) = (T - \tau - M\xi)\,\mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right)C_0. \quad (6)$$

B. ENERGY CONSUMPTION OF NETWORK

In the SCSTN, according to the cooperative sensing results and the spectrum usage, four possible energy consumption scenarios are listed in Tab.1.

TABLE 1. Four possible energy consumption scenarios.

Real state of terrestrial network/the probabilities	Fusion decision/the probabilities	Energy consumption(Joules)
Busy/$\mathcal{P}(\mathcal{H}_1)$	Busy/$\mathcal{P}(\mathcal{H}_1)Q_d$	$E_1 = M\left(p_s\tau + p_r\xi\right)$
Idle/$\mathcal{P}(\mathcal{H}_0)$	Busy/$\mathcal{P}(\mathcal{H}_0)Q_f$	$E_1 = M\left(p_s\tau + p_r\xi\right)$
Busy/$\mathcal{P}(\mathcal{H}_1)$	Idle/$\mathcal{P}(\mathcal{H}_1)\left(1 - Q_d\right)$	$E_2 = M\left(p_s\tau + p_r\xi\right) + (T - \tau - M\xi)p_t$
Idle/$\mathcal{P}(\mathcal{H}_0)$	Idle/$\mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right)$	$E_2 = M\left(p_s\tau + p_r\xi\right) + (T - \tau - M\xi)p_t$

As shown in Tab.1, in scenario 1, the fusion center successfully detects the busy state of the terrestrial network with the probability $\mathcal{P}(\mathcal{H}_1)Q_d$, and the total energy consumption is denoted as $E_1 = M\left(p_s\tau + p_r\xi\right)$, where p_s and p_r represent the sensing consumption energy and the reporting consumption energy of single satellite terminal. Under scenario 2, the terrestrial network is idle and the fusion center detects it as busy with the probability $\mathcal{P}(\mathcal{H}_0)Q_f$, no data can be transmitted and the energy consumption is also E_1. In scenario 3, the fusion center miss detects the busy state of the terrestrial network with the probability $\mathcal{P}(\mathcal{H}_1)(1 - Q_d)$. The last scenario, the terrestrial network is idle and the

fusion center detects the state correctly with the probability $\mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right)$. Therefore, in the last two scenarios, the satellite terminals can perform the data transmission and the energy consumed is given by $E_2 = M\left(p_s\tau + p_r\xi\right) + (T - \tau - M\xi)p_t$.

Therefore, the average energy consumption of the SCSTN is given by

$$\varphi(\varepsilon, \tau, k, M)$$
$$= \mathcal{P}(\mathcal{H}_1)Q_d E_1 + \mathcal{P}(\mathcal{H}_0)Q_f E_1$$
$$\quad + \mathcal{P}(\mathcal{H}_1)(1 - Q_d)E_2 + \mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right)E_2$$
$$= E_1 + E_0\mathcal{P}(\mathcal{H}_1)(1 - Q_d) + E_0\mathcal{P}(\mathcal{H}_0)\left(1 - Q_f\right) \quad (7)$$

where $E_2 = E_1 + E_0$, and $E_0 = (T - \tau - M\xi)p_t$.

C. ENERGY EFFICIENCY (EE)

In this paper, we are interested in the EE of the SCSTN, which can be expressed as

$$\eta(\varepsilon, \tau, k, M) = \frac{R(\varepsilon, \tau, k, M)}{\varphi(\varepsilon, \tau, k, M)} = \frac{\tilde{R}(\varepsilon, \tau, k, M)}{\varphi(\varepsilon, \tau, k, M)} \quad (8)$$

where $\tilde{R}(\varepsilon, \tau, k, M) = A\left(1 - Q_f(\varepsilon, \tau, k, M)\right)$, and $A = (T - \tau - M\xi)\mathcal{P}(\mathcal{H}_0)C_0$. From (8), it is obvious that the EE of the cognitive satellite network is a function of the energy detection threshold ε of the satellite terminals, the sensing duration τ, the rule threshold of fusion k and the number of distributed cooperative terminals M.

Intuitively from (8), for the given τ and M, when both Q_f and Q_d are close to zero, that is the fusion center always determines that the PU is idle, the average throughput of the satellite network can be maximized, however, the average energy consumption is also maximized. On the other hand, when both Q_f and Q_d are close to one, the average energy consumed by the satellite network is minimized, however, the average throughput becomes zero. The reason is that the fusion center always determines that the PU is active and the satellite terminal cannot utilize the spectrum. Therefore, it is necessary to optimize Q_f and Q_d by designing ε and k to maximize the EE when τ and M is fixed.

Furthermore, according to (8), the EE can be maximized when Q_f is close to zero and Q_d is close to one when τ and M are given. However, from (3)(4), Q_f and Q_d are inversely proportional to k and ε, and change in the same direction. Herein, there are two approaches to decrease Q_f while increasing Q_d. They are to increase the τ value and/or M value. With the increase in τ and/or M, the sensing performance can be better. However, due to the shorter transmission duration $T - \tau - M\xi$, the average throughput does not necessarily increase with the decreased Q_f. Besides, increasing τ and/or M may also increase the total energy consumption because of the energy consumption in scenarios 1 and 2, although the energy consumption in scenario 3 becomes smaller for the higher cooperative detection probability Q_d. Therefore, when designing τ and M, it is necessary to consider the tradeoff among sensing performance, transmission period, and energy consumption.

IV. SOLUTION OF FORMULATION

The EE of the SCSTN is related to energy detection threshold ε of the satellite terminal, the sensing duration τ, the fusion rule threshold k, and the number of distributed cooperative terminals M. In this section, we focus on how to identify k and ε to achieve the maximum EE when τ and M are fixed.

A. OPTIMAL RULE THRESHOLD OF FUSION

In the SCSTN, the satellite terminals report their sensing results to the fusion center in the reporting duration through the forward channel respectively. If there is no backward control channel between the fusion center and the satellite terminal, the fusion center cannot adjust the sensing parameters of satellite terminals to achieve the maximum EE. Thus, the distributed cooperative satellite terminals decide their ε by the predetermined p_f or p_d. After gathering the M sensing results through the forward channel, the fusion center use the k-out-of-M fusion rule to make a final decision. Herein, determining the fusion rule threshold k to maximize EE when ε is given is our focus.

Consequently, from (8), we have

$$
\begin{aligned}
&\max_{k} \eta(k) \\
&= \frac{A\left(1 - Q_f(k)\right)}{E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)\left(1 - Q_f(k)\right)} \\
&s.t. \ 0 < k \le M.
\end{aligned} \tag{9}
$$

It is obvious the ratio-type formulation (9) cannot be solved directly. According to the suggestion in the paper [43], the optimizing problem of the ratio-type objective function can be transformed into a parametric formulation, which allows us to derive a simple solution. Thus, (9) be equivalently formulated with parameters k and λ as

$$
\begin{aligned}
\phi(k, \lambda) = A\left(1 - Q_f(k)\right) &- \lambda\left(E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k))\right. \\
&\left. + E_0 \mathcal{P}(\mathcal{H}_0)\left(1 - Q_f(k)\right)\right)
\end{aligned} \tag{10}
$$

where $\lambda > 0$. The objective function can be expressed as

$$
\theta(\lambda) = \max_{k} \phi(k, \lambda). \tag{11}
$$

The relationship between the original problem and the parametric problem is discussed as follows.

Proposition 1: Denote k^* represents the optimal solution of the original (9). Then, we have $\eta(k^*) = \lambda^*$ if and only if $\theta(\lambda^*) = 0$.

Proof: For any k and $0 < k \le M$, $(1 - Q_d(k)) \ge 0$ and $\left(1 - Q_f(k)\right) \ge 0$. In this case, $E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)\left(1 - Q_f(k)\right) > 0$. When $\eta(k^*) = \lambda^*$, we have

$$
\begin{aligned}
\eta(k) &= \frac{A\left(1 - Q_f(k)\right)}{E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k))} \\
&\le \lambda^*
\end{aligned}
$$

and

$$
\begin{aligned}
\eta\left(k^*\right) &= \frac{A\left(1 - Q_f\left(k^*\right)\right)}{E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k^*)) + E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k^*))} \\
&= \lambda^*.
\end{aligned}
$$

Due to

$$
E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k)) > 0,
$$
$$
\begin{aligned}
\phi(k, \lambda^*) = A(1 - Q_f(k)) &- \lambda^*(E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) \\
&+ E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k))) \le 0
\end{aligned}
$$

and the maximum value $\theta(\lambda^*) = \max_{k} \phi(k, \lambda^*) = 0$ can be achieved when $k = k^*$.

When $\theta(\lambda^*) = 0$, and we have

$$
\begin{aligned}
A(1 - Q_f(k)) &- \lambda^*(E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) \\
&+ E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k))) \le 0
\end{aligned}
$$

and

$$
\begin{aligned}
A(1 - Q_f(k^*)) &- \lambda^*(E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k^*)) \\
&+ E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k^*))) = 0,
\end{aligned}
$$

due to

$$
\begin{aligned}
&E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k)) > 0, \ \eta(k) \\
&= \frac{A(1 - Q_f(k))}{E_1 + E_0 \mathcal{P}(\mathcal{H}_1)(1 - Q_d(k)) + E_0 \mathcal{P}(\mathcal{H}_0)(1 - Q_f(k))} \le \lambda^*.
\end{aligned}
$$

The maximum EE $\eta(k) = \lambda^*$ is achieved with $k = k^*$. ∎

From Proposition 1, if we can find a parametric problem $\theta(\lambda)$ with parameter λ^* such that the value of $\theta(\lambda^*)$ is 0, the corresponding optimal k value is also optimal for the original problem (9). Thus, the optimal k of (9) can be found by searching over the possible values of λ. The monotonicity of the parameterized problem is revealed by the following proposition, therefore effective search algorithm can be applied to obtain the optimal λ^*.

Proposition 2: $\theta(\lambda)$ is a monotonously decreasing function of λ.

Proof: For any k and $0 < k \le M$, we assume two parameters λ_1 and λ_2, and $\lambda_1 < \lambda_2$. We have $\theta(\lambda_1) = \max_{k} \phi(k, \lambda_1) \ge \phi(k, \lambda_1) \ge \phi(k, \lambda_2)$. Therefore, $\theta(\lambda_1) \ge \max_{k} \phi(k, \lambda_2) = \theta(\lambda_2)$. ∎

Since $\theta(\lambda)$ is a monotonously decreasing function of λ, the maximum value of $\eta(k^*)$ which occurs at $\theta(\eta(k^*)) = 0$ can be obtained through the bisection algorithm. Furthermore, the interval of λ can be found as follow steps. Firstly, for a given λ, the approximate differential expression with respect to k can be formulated as

$$
\begin{aligned}
\frac{\partial \phi(k, \lambda)}{\partial k} &\approx \phi(k + 1, \lambda) - \phi(k, \lambda) \\
&= \left(Q_f(k) - Q_f(k+1)\right)(A - \lambda E_0 \mathcal{P}(\mathcal{H}_0)) \\
&\quad - \left(Q_d(k) - Q_d(k+1)\right) \lambda E_0 \mathcal{P}(\mathcal{H}_1)) \\
&= \binom{M}{k} \left(p_f^k (1 - p_f)^{M-k} (A - \lambda E_0 \mathcal{P}(\mathcal{H}_0)) \right. \\
&\quad \left. - p_d^k (1 - p_d)^{M-k} \lambda E_0 \mathcal{P}(\mathcal{H}_1) \right).
\end{aligned} \tag{12}
$$

Algorithm 1

Set parameters:

$\sigma_\lambda > 0$: Error tolerances;

Initialization:

$\lambda_{\min} = 0$;

$\lambda_{\max} = A \Big/ \Big(E_0 P (\mathcal{H}_1) \left((1 - p_d)/(1 - p_f) \right)^M + E_0 P (\mathcal{H}_0) \Big)$;

$k_{\min} = 1$; $k_{\max} = M$

While $\lambda_{\max} - \lambda_{\min} > \sigma_\lambda$ or $k_{\max} \neq k_{\min}$

   Calculate $\lambda = (\lambda_{\max} + \lambda_{\min})/2$;

   Calculate k and $\theta (\lambda)$ by (13), (11), respectively;

   if $\theta (\lambda) > 0$: set $\lambda_{\min} = \lambda$, $k_{\min} = k$;

   else: set $\lambda_{\max} = \lambda$, $k_{\max} = k$;

End;

$\lambda_{\max} = \lambda$, $k_{\max} = k$

Then, the optimal k value can be calculated when $\frac{\partial \phi(k,\lambda)}{\partial k} = 0$, and k is given as

$$k = \left\lceil \frac{\log \frac{\alpha}{\beta} - M log \frac{1-p_f}{1-p_d}}{\log \frac{p_f}{1-p_f} - \log \frac{p_d}{1-p_d}} \right\rceil \quad (13)$$

where $\alpha = \lambda E_0 P(\mathcal{H}_1)$, $\beta = A - \lambda E_0 P(\mathcal{H}_0)$, and $\lceil \cdot \rceil$ represents the minimum integer that is greater than or equal to the number. Additionally, due to $k \geq 1$, the range of λ can be calculated by (14)

$$\frac{\log \frac{\alpha}{\beta} - M log \frac{1-p_f}{1-p_d}}{\log \frac{p_f}{1-p_f} - \log \frac{p_d}{1-p_d}} > 0. \quad (14)$$

Since $1 > p_d > p_f > 0$ [44], $\log \frac{p_f}{1-p_f} - \log \frac{p_d}{1-p_d} = \log \frac{p_f(1-p_d)}{p_d(1-p_f)} < 0$, and $k \geq 1$, we have

$$\log \frac{\alpha}{\beta} - M log \frac{1 - p_f}{1 - p_d} < 0. \quad (15)$$

Substituting α and β to (15), the equation can be expressed as

$$0 < \frac{\lambda E_0 \mathcal{P} (\mathcal{H}_1)}{A - \lambda E_0 \mathcal{P} (\mathcal{H}_0)} < \left(\frac{1 - p_f}{1 - p_d} \right)^M. \quad (16)$$

Due to $\lambda E_0 \mathcal{P} (\mathcal{H}_1) > 0$, then $A - \lambda E_0 \mathcal{P} (\mathcal{H}_0) > 0$. Finally, from (16), we obtain

$$\lambda < \frac{A}{\Big(E_0 P (\mathcal{H}_1) \left((1 - p_d)/(1 - p_f) \right)^M + E_0 P (\mathcal{H}_0) \Big)} \quad (17)$$

Thus, the interval of λ is

$$\left(0, \frac{A}{\Big(E_0 P (\mathcal{H}_1) \left((1 - p_d)/(1 - p_f) \right)^M + E_0 P (\mathcal{H}_0) \Big)} \right).$$

Considering the monotonicity of $\theta (\lambda)$, the interval $[\lambda_{\min}, \lambda_{\max}]$ contains the optimal λ^*. According to the bisection algorithm, at each λ within the interval, we iterate λ, k and calculate the parametric problem $\theta (\lambda)$. The iteration ends

when $(\lambda_{\max} - \lambda_{\min}) < \sigma_\rho$ and $k_{\min} = k_{\max}$, where σ_ρ is the tolerable error of λ.

B. OPTIMAL ENERGY DETECTION THRESHOLD

Since the sensing performance of the satellite terminal has an effect on the EE in the SCSTN, when the fusion center has a backward control channel, it can adjust the sensing performance at each satellite terminal through the backward control channel. Specifically, the fusion center can control the energy detection threshold ε of the satellite terminal, the sensing duration τ, and the number of distributed cooperative terminals M through the backward control channel to maximum the EE of the network. In this part, we are interest in obtaining the optimal detection threshold ε of the satellite terminals when other parameters are fixed. Therefore, according to (8), the problem formulation is given by

$$\max_{\varepsilon} \eta (\varepsilon)$$

$$= \frac{A \left(1 - Q_f (\varepsilon) \right)}{E_1} + E_0 \mathcal{P} (\mathcal{H}_1) \left(1 - Q_d (\varepsilon) \right) + E_0 \mathcal{P} (\mathcal{H}_0)$$

$$\times \left(1 - Q_f (\varepsilon) \right). \quad (18)$$

The optimal solution of ε can be obtained by solving $\frac{\partial \eta(\varepsilon)}{\partial \varepsilon} = 0$. Thus, we have

$$1 - Q_d (\varepsilon) - (1 - Q_f (\varepsilon)) \frac{Q_d{}' (\varepsilon)}{Q_f{}' (\varepsilon)} + \frac{E_1}{E_0 \mathcal{P} (\mathcal{H}_1)} = 0. \quad (19)$$

From (3) and (4), the differential of $Q_d (\varepsilon)$ and $Q_f (\varepsilon)$ can be expressed as

$$Q_f{}' (\varepsilon) = \frac{\partial Q_f (\varepsilon)}{\partial \varepsilon}$$

$$= p_f{}' \sum_{m=k}^{M} \binom{M}{m} p_f{}^{m-1} \left(1 - p_f \right)^{M-m}$$

$$\times \left(m - (M - m) \frac{p_f}{1 - p_f} \right) \quad (20)$$

and

$$Q_d{}' (\varepsilon) = \frac{\partial Q_d (\varepsilon)}{\partial \varepsilon}$$

$$= p_d{}' \sum_{m=k}^{M} \binom{M}{m} p_d{}^{m-1} (1 - p_d)^{M-m}$$

$$\times \left(m - (M - m) \frac{p_d}{1 - p_d} \right) \quad (21)$$

where

$$p_f{}' (\varepsilon) = \frac{\partial p_f}{\partial \varepsilon}$$

$$= \frac{-1}{\sigma_n^2} \sqrt{\frac{\tau f_s}{2\pi}} \exp \left(-\frac{\tau f_s}{2} \left(\frac{\varepsilon}{\sigma_n^2} - 1 \right)^2 \right) \quad (22)$$

and

$$p_d{'}(\varepsilon) = \frac{\partial p_d}{\partial \varepsilon} = \frac{-1}{\sigma_n^2} \sqrt{\frac{\tau f_s}{2\pi (2\gamma + 1)}}$$

$$\times \exp\left(-\frac{\tau f_s}{4\gamma + 2}\left(\frac{\varepsilon}{\sigma_n^2} - \gamma - 1\right)^2\right). \quad (23)$$

The optimal solution of ε can be obtained by substituting equations (20)-(23) into (19) and solve (19).

C. COMPUTATIONAL COMPLEXITY

An algorithm to obtain the optimal rule threshold k for the problem is developed. Another way to find the optimal k is to exhaustively search over all the possible rule thresholds of fusion. Specifically, for the given energy detection threshold ε of each satellite terminals, we can exhaustively compute the EE for all the possible k ($1 \leq k \leq M$). Then we choose the optimal k that gives the maximum EE. The computational complexity of the exhaustive search is $O(M)$ and the bisection algorithm proposed in part A of this section is $O(\beta)$, where $\beta = \left\lceil \log_2\left(\frac{\lambda_{max} - \lambda_{min}}{\sigma_\lambda}\right)\right\rceil$ is the number of iterations that the bisection search algorithm takes to terminate and $\lceil (\cdot) \rceil$ represents the smallest integer not less than $(\cdot)$. The average number of iterations for the algorithm to converge for $N = 1$ to $N = 100$ is just 7.0133. Besides, for the k and ε joint optimization, the computational complexity is also $O(M)$, since we first calculate the energy detection threshold ε of the satellite terminals for each k value, then calculate the EE, finally determine the maximum EE and the corresponding ε and k.

V. SIMULATION RESULTS AND ANALYSIS

Simulations are carried out with MATLAB R2017a and in this section numerical simulation results are presented to evaluate the EE of SCSTN with the proposed optimal methods. The simulation parameters are shown in Tab.2 unless otherwise stated [44]–[46].

TABLE 2. Simulation parameters.

Parameters	Values
Frame duration T	20ms
Sensing duration τ	1ms
Reporting duration ξ	0.01ms
PU idle probability $P(\mathcal{H}_0)$	0.7
False alarm probability p_f	0.1
Sample frequency f_s	6MHz
Sensing power p_s	0.1W
Reporting power p_r	0.3W
Transmit power p_t	2W
SCSTN throughput when PU is inactive C_0	6.658bps/Hz
Number of distributed cooperative terminals M	25

When the ε of each satellite terminals are given by the predetermined p_f, Fig. 3 presents the optimal k values obtained by the paper proposed method and the exhaustive search method. It is clear that k increases with the increase in M and the same k value can be obtained by these two methods, which shows that the paper proposed method can obtain the optimal k value. Besides, under the same conditions, when γ is lower, as M increases, k increases faster.
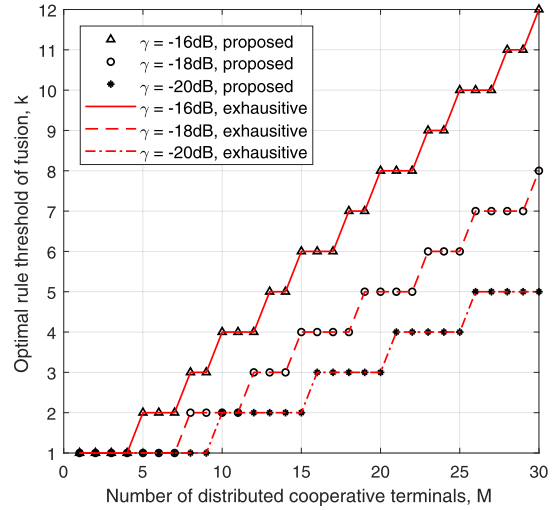

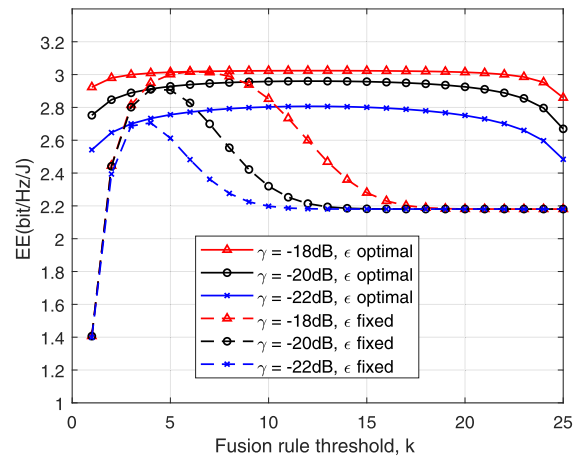**FIGURE 3.** The optimal k value versus M for different γ.

FIGURE 4. EE versus k for different scenarios when $M = 25$.

In Fig. 4, for the given M, we compare the trend of EE versus k with the different γ when ε is fixed or optimal. It is noticed that when ε of the satellite terminal can be optimized by the fusion center through the backward control channel, the trend of EE is relatively flat, where it seems that the optimal k is no longer as important in this scenario. Besides, if there is no backward control channel and ε is fixed by the predetermined p_f, with the increase in k, the EE first increases and becomes decreasing after the optimal k, which corresponds to the maximum EE. Compared with the scenario that ε is optimized, it is not difficult to observe that k has a

greater influence on EE when ε is fixed. For example, under the conditions of $\gamma = -20dB$ and ε is fixed, the EE value of $k = 4$ is more than double than that of when $k = 1$. This can be explained as follows. When the k is small, the transmission opportunity is missed for the higher cooperative false alarm probability. Thus, the average throughput is small and EE is also reduced. When the k increases over the optimal value, since the reduced cooperative false alarm probability and consequently increased average throughput may not be able to offset the increased spectrum sensing energy consumption, the EE decreases. Hence, a trade-off phenomenon can be observed. Besides, it is interesting that regardless of whether the ε value is optimal or not, the difference in the maximum EE of the network is very small in these two scenarios. Consequently, it is worth considering when the fusion center has the ability to optimize k, is it necessary to optimize ε of satellite terminals through the backward control channel?
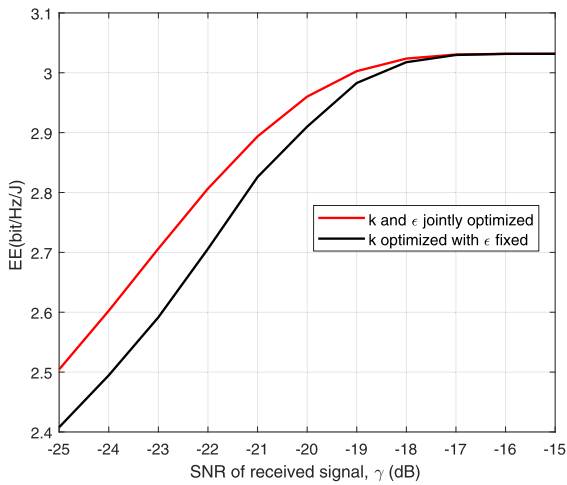

FIGURE 6. EE versus τ for different γ.

FIGURE 5. EE versus γ for different scenarios.

Fig. 5 depicts the trend of EE with an increase of γ in different scenarios. It is obvious that the EE increases with an increase of γ. Additionally, it is also seen that when γ is lower, the EE achieved under the condition that k and ε are jointly optimized is larger than that achieved under the condition that k is optimized while ε is fixed. However, when γ is in a high region, the difference of EE in the two scenarios is smaller. Therefore, we can conclude that when γ is high, it is more efficient to maximize the EE by optimizing k at the fusion center, which is not necessary to have the backward control channel to adjust the ε of satellite terminals.

Furthermore, with the increase of the sensing duration τ and the number of distributed cooperative terminals M, the sensing performance is better. However, the energy consumption increases, and the transmission time is shorter for the fixed frame duration. Herein, the simulations that the EE versus τ and M for different γ are given in Fig. 6 and Fig. 7, respectively.

In Fig. 6, with the increase in τ, the EE increases first and decreases after the optimal sensing time. The reason is
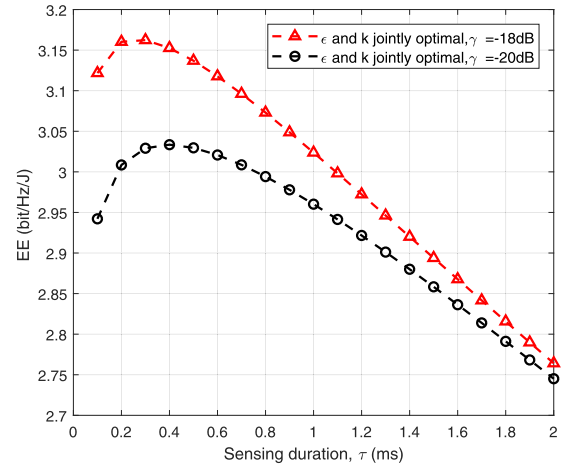
that at the beginning the improving sensing performance can outweigh the loss in the shortened transmission duration and the increased sensing energy consumption. However, after the optimal sensing duration, increasing energy consumption and shortened transmission duration can degrade the EE performance. Hence it is not worth increasing the sensing duration after the optimal sensing duration. Besides, it is obvious that with the increase in γ, the optimal τ value corresponding to the maximum EE is shorter.

In Fig. 7, it is clear that the EE trends are similar to that in Fig. 6. The result can be explained that the effect of M on the EE is similar to that of τ. And it is not difficult to observe that the higher γ, the larger EE for the same M. Furthermore, with the increase in γ, the optimal M value corresponding to the maximum EE is smaller. For example, when $\gamma = -18dB$ and $\gamma = -20dB$, the corresponding optimal M are 11 and 16, respectively. This indicates that γ is higher, the better sensing performance also can be obtained even M is smaller. Therefore, since the optimal M value can
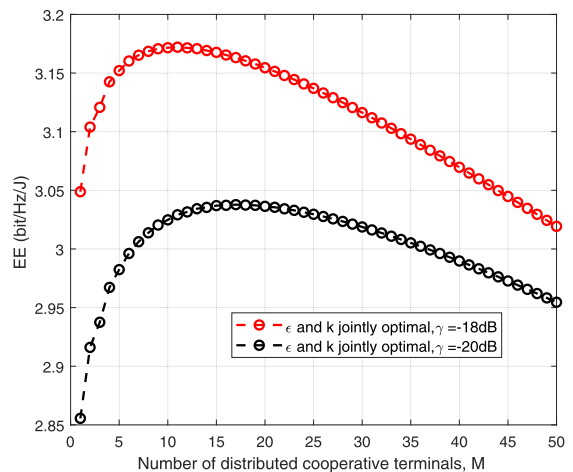

FIGURE 7. EE versus M for different γ.

be obtained, the satellite terminals in the SCSTN can perform spectrum sensing task in turn and thereby extend battery life.

VI. CONCLUSION

In this paper, a novel sensing-based cognitive satellite terrestrial network architecture is proposed, which integrates the distributed cooperative sensing network with the cognitive satellite terrestrial network. Then, the EE formulation of the cognitive satellite network based on the distributed cooperative sensing results is presented, which is related to the rule threshold of fusion k, the energy detection threshold of the sensing node ε, the sensing duration τ and the number of distributed cooperative terminals M. Subsequently, to obtain the optimal k, we transform the ratio-type EE formulation to the parametric formulation. An algorithm for the optimal k has been developed by exploring the relationship between the two formulations and making use of the monotonicity property of the parametric formulation. We have further investigated the optimal ε of EE, and discuss the effect of τ and M on the EE. Simulations have shown when ε is fixed, the EE can obtain more than double gain by only optimizing k. Additionally, when γ is in the high region, it is more efficient to maximize the EE by optimizing k at the fusion center. Moreover, it has been found that the value of M has an optimal threshold, which indicates that some satellite terminals are enough to perform sensing, therefore the satellite terminals in SCSTN can perform sensing in turn and thereby increasing their battery life.

REFERENCES

[1] S. Shi, G. Li, K. An, Z. Li, and G. Zheng, "Optimal power control for real-time applications in cognitive satellite terrestrial networks," *IEEE Commun. Lett.*, vol. 21, no. 8, pp. 1815–1818, Aug. 2017.

[2] F. Zhou, Y. Wu, Y.-C. Liang, Z. Li, Y. Wang, and K.-K. Wong, "State of the art, taxonomy, and open issues on cognitive radio networks with NOMA," *IEEE Wireless Commun.*, vol. 25, no. 2, pp. 100–108, Apr. 2018.

[3] M. Jia, X. Liu, X. Gu, and Q. Guo, "Joint cooperative spectrum sensing and channel selection optimization for satellite communication systems based on cognitive radio," *Int. J. Satell. Commun. Netw.*, vol. 35, no. 2, pp. 139–150, Mar. 2017.

[4] S. Chatzinotas, B. Evans, A. Guidotti, V. Icolari, E. Lagunas, S. Maleki, S. K. Sharma, D. Tarchi, P. Thompson, and A. Vanelli-Coralli, "Cognitive approaches to enhance spectrum availability for satellite systems," *Int. J. Satell. Commun. Netw.*, vol. 35, no. 5, pp. 407–442, Sep. 2017.

[5] J. Mitola and G. Q. Maguire, "Cognitive radio: Making software radios more personal," *IEEE Pers. Commun.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[6] H. Hu, Y. Huang, Y. Da, H. Zhang, L. Ni, and Y. Pan, "Optimization of energy management for UAV-enabled cognitive radio," *IEEE Wireless Commun. Lett.*, early access, May 18, 2020, doi: 10.1109/LWC.2020.2995226.

[7] H. Hu, X. Da, Y. Huang, H. Zhang, L. Ni, and Y. Pan, "SE and EE optimization for cognitive UAV network based on location information," *IEEE Access*, vol. 7, pp. 162115–162126, 2019.

[8] M. Jia, X. Gu, Q. Guo, W. Xiang, and N. Zhang, "Broadband hybrid satellite-terrestrial communication systems based on cognitive radio toward 5G," *IEEE Wireless Commun.*, vol. 23, no. 6, pp. 96–106, Dec. 2016.

[9] A. Goldsmith, S. A. Jafar, I. Maric, and S. Srinivasa, "Breaking spectrum gridlock with cognitive radios: An information theoretic perspective," *Proc. IEEE*, vol. 97, no. 5, pp. 894–914, May 2009.

[10] X. Kang, Y.-C. Liang, H. Krishna Garg, and L. Zhang, "Sensing-based spectrum sharing in cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 58, no. 8, pp. 4649–4654, Oct. 2009.

[11] L. Boero, M. Marchese, and F. Patrone, "The impact of delay in software-defined integrated terrestrial-satellite networks," *China Commun.*, vol. 15, no. 8, pp. 11–21, Aug. 2018.

[12] B. Zhao, C. Fei, X. Mao, W. Yu, and C. Wu, "Networking in space terrestrial integrated networks," in *Proc. 18th Int. Conf. Opt. Commun. Netw. (ICOCN)*, Aug. 2019, pp. 1–3.

[13] Y. Gao, Q. Ou, Q. Zeng, X. Zhang, and J. Wu, "Analysis of mutual interferences between two components in satellite-terrestrial integrated system," in *Proc. 3rd Int. Conf. Consum. Electron., Commun. Netw.*, Nov. 2013, pp. 145–148.

[14] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Satellite cognitive communications: Interference modeling and techniques selection," in *Proc. 6th Adv. Satell. Multimedia Syst. Conf. (ASMS) 12th Signal Process. Space Commun. Workshop (SPSC)*, Sep. 2012, pp. 111–118.

[15] J. Hu, G. Li, D. Bian, L. Gou, and C. Wang, "Optimal power control for cognitive LEO constellation with terrestrial networks," *IEEE Commun. Lett.*, vol. 24, no. 3, pp. 622–625, Mar. 2020.

[16] E. Lagunas, S. K. Sharma, S. Maleki, S. Chatzinotas, and B. Ottersten, "Resource allocation for cognitive satellite communications with incumbent terrestrial networks," *IEEE Trans. Cognit. Commun. Netw.*, vol. 1, no. 3, pp. 305–317, Sep. 2015.

[17] K. An, M. Lin, W.-P. Zhu, Y. Huang, and G. Zheng, "Outage performance of cognitive hybrid satellite–terrestrial networks with interference constraint," *IEEE Trans. Veh. Technol.*, vol. 65, no. 11, pp. 9397–9404, Nov. 2016.

[18] S. Vassaki, M. I. Poulakis, A. D. Panagopoulos, and P. Constantinou, "Power allocation in cognitive satellite terrestrial networks with QoS constraints," *IEEE Commun. Lett.*, vol. 17, no. 7, pp. 1344–1347, Jul. 2013.

[19] K. An, T. Liang, G. Zheng, X. Yan, Y. Li, and S. Chatzinotas, "Performance limits of cognitive-uplink FSS and terrestrial FS for ka-band," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 55, no. 5, pp. 2604–2611, Oct. 2019.

[20] V. Singh and P. K. Upadhyay, "Cognitive hybrid satellite-terrestrial relay networks with simultaneous energy and information transmission," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, Dec. 2018, pp. 1–6.

[21] R. Engelman, K. Abrokwah, and G. Dillon, "Federal communications commission spectrum policy task force report of the spectrum efficiency working group," *Federal Commun. Commission Spectr. Policy Task Force*, vol. 1, no. 1, p. 37, 2002.

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

[23] S. Stotas and A. Nallanathan, "On the throughput and spectrum sensing enhancement of opportunistic spectrum access cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 11, no. 1, pp. 97–107, Jan. 2012.

[24] S. K. Sharma, T. E. Bogale, L. B. Le, S. Chatzinotas, X. Wang, and B. Ottersten, "Dynamic spectrum sharing in 5G wireless networks with full-duplex technology: Recent advances and research challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 674–707, 1st Quart., 2018.

[25] T. E. Bogale, L. Vandendorpe, and L. Le, "Sensing throughput tradeoff for cognitive radio networks with noise variance uncertainty," in *Proc. 9th Int. Conf. Cognit. Radio Oriented Wireless Netw.*, 2014, pp. 435–441.

[26] W. Zhang, R. Mallik, and K. Letaief, "Optimization of cooperative spectrum sensing with energy detection in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 12, pp. 5761–5766, Dec. 2009.

[27] P. Amirshahi, P. Ransom, S. Grippando, and I. Navarro, "Comparison of centralized and distributed spectrum monitoring methods for enabling spectrum sharing between weather satellites and terrestrial networks," in *Proc. IEEE Int. Symp. Dyn. Spectr. Access Netw. (DySPAN)*, Nov. 2019, pp. 1–8.

[28] S. Chaudhari, J. Lunden, V. Koivunen, and H. V. Poor, "Cooperative sensing with imperfect reporting channels: Hard decisions or soft decisions?" *IEEE Trans. Signal Process.*, vol. 60, no. 1, pp. 18–28, Jan. 2012.

[29] J. So, "Cooperative spectrum sensing with two-stage reporting for cognitive radio networks," *Electron. Lett.*, vol. 52, no. 1, pp. 83–85, Jan. 2016.

[30] H. Hu, H. Zhang, and H. Yu, "Delay QoS guaranteed cooperative spectrum sensing in cognitive radio networks," *AEU-Int. J. Electron. Commun.*, vol. 67, no. 9, pp. 804–807, Sep. 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1434841113001015

[31] Y. Chen, N. Zhang, Y. Zhang, X. Chen, W. Wu, and X. S. Shen, "Energy efficient dynamic offloading in mobile edge computing for Internet of Things," *IEEE Trans. Cloud Comput.*, early access, Feb. 11, 2019, doi: 10.1109/TCC.2019.2898657.

[32] Y. Ruan, Y. Li, R. Zhang, W. Cheng, and C. Liu, "Cooperative resource management for cognitive satellite-aerial-terrestrial integrated networks towards IoT," *IEEE Access*, vol. 8, pp. 35759–35769, 2020.

[33] F. Alagoz and G. Gur, "Energy efficiency and satellite networking: A holistic overview," *Proc. IEEE*, vol. 99, no. 11, pp. 1954–1979, Nov. 2011.

[34] W. Li, M. Li, and Y. Hao, "A high reliable satellite communication for emergency communications," in *Proc. IET Int. Conf. Commun. Technol. Appl. (ICCTA)*, 2011, pp. 811–814.

[35] D. Feng, C. Jiang, G. Lim, L. J. Cimini, G. Feng, and G. Ye Li, "A survey of energy-efficient wireless communications," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 167–178, 1st Quart., 2013.

[36] C. Jiang, H. Zhang, Y. Ren, and H.-H. Chen, "Energy-efficient non-cooperative cognitive radio networks: Micro, Meso, and macro views," *IEEE Commun. Mag.*, vol. 52, no. 7, pp. 14–20, Jul. 2014.

[37] A. C. Fu, E. Modiano, and J. N. Tsitsiklis, "Optimal energy allocation and admission control for communications satellites," *IEEE/ACM Trans. Netw.*, vol. 11, no. 3, pp. 488–500, Jun. 2003.

[38] T. Qi and Y. Wang, "Energy-efficient power allocation over multibeam satellite downlinks with imperfect CSI," in *Proc. Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2015, pp. 1–5.

[39] J. Zhang, B. Evans, M. A. Imran, X. Zhang, and W. Wang, "Green hybrid satellite terrestrial networks: Fundamental trade-off analysis," in *Proc. IEEE 83rd Veh. Technol. Conf. (VTC Spring)*, May 2016, pp. 1–5.

[40] U. Park, H. W. Kim, D. S. Oh, and D.-I. Chang, "Performance analysis of dynamic resource allocation for interference mitigation in integrated satellite and terrestrial systems," in *Proc. 9th Int. Conf. Next Gener. Mobile Appl., Services Technol.*, Sep. 2015, pp. 217–221.

[41] V. Deslandes, J. Tronc, and A.-L. Beylot, "Analysis of interference issues in integrated satellite and terrestrial mobile systems," in *Proc. 5th Adv. Satell. Multimedia Syst. Conf. 11th Signal Process. Space Commun. Workshop*, Sep. 2010, pp. 256–261.

[42] X. Wu, J. Xu, M. Chen, and J. Wang, "Optimal energy-efficient sensing and power allocation in cognitive radio networks," *Math. Problems Eng.*, vol. 2014, pp. 1–6, Aug. 2014.

[43] Y. Pei, Y.-C. Liang, K. C. Teh, and K. H. Li, "Energy-efficient design of sequential channel sensing in cognitive radio networks: Optimal sensing strategy, power allocation, and sensing order," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1648–1659, Sep. 2011.

[44] H. Hu, H. Zhang, and Y.-C. Liang, "On the spectrum- and energy-efficiency tradeoff in cognitive radio networks," *IEEE Trans. Commun.*, vol. 64, no. 2, pp. 490–501, Feb. 2016.

[45] V. Greshma and T. Sudha, "Energy harvesting aided localization for green cognitive radio network," in *Proc. IEEE Int. Conf. Intell. Techn. Control, Optim. Signal Process. (INCOS)*, Mar. 2017, pp. 1–8.

[46] X. Li, J. Cao, Q. Ji, and Y. Hei, "Energy efficient techniques with sensing time optimization in cognitive radio networks," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2013, pp. 25–28.

GUANGXIA LI received the B.S. and M.S. degrees from the Institute of Communication Engineer, Nanjing, China, in 1983 and 1986, respectively. He is currently a Professor with the College of Communication Engineering, Army Engineering University of PLA, Nanjing. His current research interests include design of communication systems, satellite communications, satellite navigation, communication anti-jamming, and satellite TT&C.

DONGMING BIAN received the Ph.D. degree from the PLA University of Science and Technology, Nanjing, China, in 2004. He is currently a Professor with the College of Communication Engineering, Army Engineering University of PLA, Nanjing. His research interests include wireless communications, satellite communications, and deep space communications.

SHENGCHAO SHI received the B.S. (Hons.), M.S. (Hons.), and Ph.D. degrees in communication and information system from the Army Engineering University of PLA, Nanjing, in 2011, 2014, and 2017, respectively. His current research interests include satellite communications, satellite TT&C, and satellite navigation.
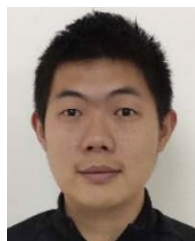
RUIXING GE received the B.S. degree from the Electronic Engineering Institute of PLA, Hefei, China, in 2014, and the M.S. degree from the National University of Defense Technology, Hefei, in 2017. He is currently pursuing the Ph.D. degree in information and communication engineering with the Army Engineering University of PLA, Nanjing, China. His research interests include hybrid terrestrial-satellite communications, multi-layered satellite networks, non-orthogonal multiple access (NOMA), and optimization techniques.

JING HU received the B.S. and M.S. degrees from the Nanjing University of Posts and Telecommunications, Nanjing, China, in 2003 and 2007, respectively. She is currently pursuing the Ph.D. degree with the College of Communications Engineering, Army Engineering University of PLA, Nanjing. Her current research interests include wireless communications, satellite communications, and communication anti-jamming.

LIANG GOU received the M.S. and Ph.D. degrees from the PLA University of Science and Technology (PLAUST), China, in 2008 and 2010, respectively. He is currently an Engineer with Nanjing Smart Constellation Information Technology Company Ltd. His research interests include satellite communications, deep space communications, space information networks, satellite constellation, and network coding.

• • •