Received July 3, 2020, accepted July 27, 2020, date of publication July 30, 2020, date of current version August 13, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3013034

Optimization of Resource Allocation Model With Energy-Efficient Cooperative Sensing in Green Cognitive Radio Networks

ARASH OSTOVAR[1], YOUSAF BIN ZIKRIA[2], (Senior Member, IEEE), HYUNG SEOK KIM[3], (Member, IEEE), AND RASHID ALI[4], (Member, IEEE)

[1]Department of Electrical and Electronics Engineering, Shiraz University of Technology, Shiraz 7155713876, Iran
[2]Department of Information and Communication Engineering, Yeungnam University, Gyeongsan 38541, South Korea
[3]Department of Information and Communication Engineering, Sejong University, Seoul 05006, South Korea
[4]School of Intelligent Mechatronics Engineering, Sejong University, Seoul 05006, South Korea

Corresponding authors: Rashid Ali (rashidali@sejong.ac.kr) and Hyung Seok Kim (hyungkim@sejong.ac.kr)

This work was supported in part by the National Research Foundation of Korea (NRF) grant funded by the Korean Government (MSIT) under Grant 2019R1A4A1023746 and Grant 2019R1F1A1060799; and in part by the Strengthening Research and Development Capability Program of Sejong University.

ABSTRACT Green cognitive radios show promise for high energy efficiency (EE) in the future of wireless communications. Spectrum sensing refers to an energy-consuming procedure that allows cognitive users to independently identify unused radio spectrum segments and prevent interference to primary users, and it should be minimized due to resource limitations. In this paper, we present a wireless multiple-access channel function to establish the primary users' presence and the mean EE optimization problem of the cognitive radio systems with mathematical structure computation purposes. EE, as the average throughput to the average energy consumption ratio, is used to measure the network's performance subject to detection constraint. More specifically, since secondary users are generally battery-powered devices, saving on energy is crucial. We aim to decrease the energy consumption of secondary users while maximizing the total EE and preserving the accurate sensing by maximizing the sensing time detection subject to secondary user power constraints and minimum data rate. To address the non-convexity optimization problem, one can consider energy-efficient power allocation based on an iterative method. Simulation results show the optimum of our framework when combined by the multiple-access channel computation-based scheme. Green cognitive radio should consider the tradeoff against its complexity and maximum available EE metric. However, one can observe from the simulation results that the improved EE presented in this work yields much higher when compared with others with the same detection performance.

INDEX TERMS Cooperative sensing, energy detection, resource allocation, spectrum sharing, energy efficiency.

I. INTRODUCTION

The development of new wireless services has, in recent years, led to increasing demand for the spectrum. Already rare in nature, the radio spectrum has had most of its practical part used by different services. Regulators are finding it more challenging to provide the capacity in the preferred frequency band for new wireless services. Spectrum sensing is a critical and fundamental function of *cognitive radios* (CRs) for the secondary user (SU) to identify available spectrum holes and avoid harmful interference to the primary user (PU). Cooperative sensing can apply independent observations at sensing nodes to raise the spectrum sensing accuracy band of interest. Moreover, it can forward the local statistics to the fusion center (FC) to decide the PUs status [1]. Green communication can reduce carbon dioxide (CO_2) emissions to protect the environment. Due to the rapid growth of the wireless networking industry, new technologies are also evolving and surpassing the old technology with higher data transfer speeds and overcoming more and more services

The associate editor coordinating the review of this manuscript and approving it for publication was Zhenyu Zhou.

on one platform. In these processes, total energy consumption by communication devices also increases significantly by 16-20% per annum, almost doubles every five years. Thus, reducing the future wireless communications energy consumption demands more considerable attention, which requires new technologies and solutions, became an essential factor of future standards specification. Development of CR technology aimed at the spectrum scarcity issue, initially. However, this technology could be an optimal option for green communications due to its built-in properties, including rigorous energy constraint and opportunistic spectrum sharing with PUs with no harmful interference.

CR is marked by an adaptive, multidimensional aware, and independent radio appointed by modern intelligent functionality, which combines with its operating era and learns from its experiences to reason, plan, and decides future actions to encounter various requirements [2]. This approach moderates a consequential enlarge in the spectrum, networking efficiency, and energy efficiency (EE). The importance of EE optimization in CR networks is numerous. Still, the design, green communications policy, savings as regards to monetary cost, and end user's gratification and fulfillment are the issues to be addressed. The wireless devices convert the consumed energy into heat, so that the more power they use, the more heat they produce. There are also worrisome problems like green-house gas (GHG), which have gained considerable global attention. More energy consumption can increase the production of GHG. Therefore, applying EE protocols in CR networks can reduce energy consumption and also be easily certified by the EE standards. Therefore, CR can play an essential role in improving EE in wireless networks, because from a green perspective, the spectrum is a natural resource that should not be wasted but be shared. The main goal of CR is to provide adaptability to the wireless transmission through *dynamic spectrum access* (DSA) so that the performance of wireless transmission can be optimized, as well as enhancing the utilization of the frequency spectrum. Target radio spectrum information would be obtained by utilizing the CRs through spectrum sensing. The sensing information is developed using spectrum management to analyze the opportunities and decision making on spectrum access. If the target spectrum status changes, the spectrum mobility function would control the evolution of operational frequency bands for the CR users [3]. Here, the CRs would identify opportunities autonomously. Today's standards and regulations must strictly restrict parameters like specified power level and frequency range in operation to obtain a minimum interoperability level, spectrum efficiency, and fair access to spectrum [2].

In cooperative spectrum sharing, the PUs needs to know whether the SU is present or not. When the PU is about to operate, it chooses other unoccupied sub-channels without restricting the SU communications. In opportunity spectrum sharing, to have information about the situation of the SU, the PU has to communicate with SUs. Nonetheless, in the case the SU is required to have access to the licensed frequency band, the PU's presence status has to be detected. If the PU occupies the licensed frequency, the unlicensed user cannot access the spectrum. On the other hand, when the PU reoccupies the frequency band, the unauthorized user demands to quit immediately and look for a new unoccupied frequency band [2]. CR devices in cooperative spectrum sensing send their decisions or local statistics to an FC, based on the type of information provided to the FC. So, cooperative sensing can be mainly classified into two aspects: hard and soft combinations. In hard combinations, SUs turn the local decisions into a one-bit decision and send these decisions to the FC. In contrast, SUs send their local statistical information, which is the amount of energy value of the received signals from the PU, to the FC in soft combination [4].

A. RELATED WORKS

In the literature, most papers have tended some schemes and algorithms to maximize the EE of the CRs. One of the issues which are being considered in recent researches in the field of green communications of future mobile networks is the maximization of EE. Here, we give a brief overview of the related works with the state-of-the-art schemes and algorithms adopted in the existing literature. To maximize EE, whereas encountered the required detection accuracy, [5] proposed an iterative algorithm to change the fusion threshold on optimal sensing length. The authors showed their proposed parameters while satisfying the detection accuracy constraints for EE maximization. However, the problems of sensing time optimization for power allocation transmission were investigated in [6] to maximize the EE and thereby, decrease the cost and sensing period. In [7], they considered a scenario where multiple SUs jointly sensed a licensed band that can be separated into multiple sub-bands. They concentrate, nevertheless, on EE maximization of power allocation and sensing time joint optimization and do not interfere mainly with the PU. To solve their optimization problem, the authors of [7] also proposed a fractional programming optimization algorithm. Wang *et al.* [8] studied the mean EE maximization problem for hard decisions, using hybrid spectrum sharing. Sensing time iterative optimization and cooperative SUs numbers can lead to the problem of the mean formulation of maximum EE. This optimization uses the following parameters: the average transmission power of SUs, peak transmission power, data rate constraints, and the mean PU interference power constraint.

In [9], the researchers proposed EE by reducing the power of the secondary transmitter for such spectrum sensing and sharing over fading situations. However, the extra channel state information (CSI) effects the secondary antenna has also been analyzed under spectrum sharing through closed-form expressions for relevant transmission power. However, imperfect cross CSI, where a licensed band is shared between those primary and secondary links, was discussed. Here, the allocation of power over perfect and imperfect measurement was reduced. However, previous studies [7], [10], [11] were examined such methods from the EE time maximization problem and power allocation joint optimization of the allowable spectrum in the presence of different CSI levels point of view, regarding the standard links of transmission and inference over statistical relationships. In [11], a novel computation over the multiple-access channel (CoMAC) was formulated to maximize the EE optimization problem. The authors also proposed an iterative solution algorithm (ISA) arrive, combining the modulated symbol sequence and efficient sensing time duration. The ISA turns the optimization problem into two sub-problems to reach the convergence. For a given symbol sequence length, they proved a sensing time quasi-convexity optimization problem and provided a bisection based algorithm as a solution. They established the optimal symbol sequence length optimization problem using an extensive search.

The authors of [12] investigated an energy-efficient resource allocation (RA) problem for energy harvesting M2M communications through the two-stage energy-efficient joint channel selection, peer discovery, power control, and time allocation algorithm. They have also combined their approach using the linear and non-linear programming, and iterative pricing based matching theory to superior the performance of the network to maximize the EE. Besides, Zhou *et al.* [13] provided a hybrid RA for D2D communications deployment as LTE-A networks based on C-RAN architectures, which include common centralized interference mitigation that was performed in the centralized BBU pool and a distributed joint channel selection and power allocation algorithm. In [14], the optimal RA strategies for delay-insensitive and -sensitive are considered to optimize the available EE, using the two proposed algorithms upon optimal RA with low complexity average metric constraint. Besides, the authors of [15] proposed optimal linear weights and optimal power allocation for SUs, to maximize the CR systems probability of detection. They also derived signal probability of PUs of high detection and high spectrum utilization using the modification of the time slots period inside of the time frame [16]. The multichannel sensing and RA problems guarantee a certain level of PUs activation protection was addressed in [17], [18] using a proportional optimization problem with CSI sensing to control the transmission power.

B. MOTIVATION AND CONTRIBUTIONS

In this paper, we attempt to solve the problem of computing functions over a wireless MAC, which has a set number of sensor nodes and an individual receiver, which we refer to as the FC. Current sensor networks often employ a tried technique to tackle this computational problem, allowing separate nodes individually transmit, in the form of a stream of information-bearing symbols, a quantized version of its data (i.e., sensor readings) to the FC. Each sensor node transmits data at a rate that is congruent with the FC reconstructing each of the (quantized) sensors reading without fault and goes on to determine the required function. Therefore, the two processes of data transmission and the function computation have no element at all in common. Protocols of the separation-based medium access type are, for the most part, greatly suboptimal, e.g., at times when maximizing computation throughput means the rate of reconstruction of quantized sensor readings at the FC that has a few communication constraints.

The information-theoretic result of [19], specifically, proposes that if the MAC mathematically corresponds to a function under calculation, the superposition property of the wireless channel can present advantageous implications. The term CoMAC refers to this method, and it can act as a technique for combining the data transmission and function computation processes through utilizing channel collisions in which concurrent access of separate nodes induces to a common channel. This technique promptly results in a higher computation throughput, hence a decreased latency or fewer bandwidth requirements. The wireless channel has superposition properties, which can make the wireless MAC suitable as a summation-type linear operator mapping the input space to the set of complex-valued numbers. Functions naturally matched to this channel, therefore, are linear functions and comprise a single class of functions of interest in practice. Nevertheless, to ensure such a perfect synchronization in practical wireless networks, it may present high costs and difficulty in providing the resources.

This paper, in general, shows the topic of EE maximization for green CR practical networks with less energy consumption. Some research works have performed EE maximization in the sensing period, transmission period, and overall EE by considering the probability of detection with closed-form expression for maximal EE. In this paper, we analyzed a different sensing method at each period with the same bandwidth on an effective coefficient for the sensing case. Then, we develop the EE of the CR performance to maximize the EE while increasing the average throughput. Therefore, our contribution is to find a procedure to reduce the CR energy consumption while maximizing total EE to protect PU comparing the other works with closed-form expressions. The basic idea behind the regime for efficient computation of desired proposed functions is to exploit the broadcast property of MAC to allow the FC to observe a superposition of signals transmitted by the CRs. Numerical comparisons with an existing method such as ISA is presented for performance analysis in EE maximization. However, the analysis in [11] is just limited to cooperative CoMAC signals based on an analytical framework. However, in this work, we have considered the collaborative sensing utility to guarantee energy saving and detection performance, which yields improvement in EE to a greater scope. To the best of our knowledge, such an analysis of EE in multichannel wireless MAC networks, including data transmission, has not been considered earlier in the literature. The main contributions of this work are summarized as follows:

- We first mathematically model the CoMAC-based approach to accelerate the practical CR sensing model to guarantee the soft sensing decision fusion to perform the EE maximization. Then, the derivatives of false alarm and detection probabilities are raised to metric the system performance. Moreover, we arrive at an optimal detection closed-form expression to achieve a simplified EE maximization problem by minimizing the average energy consumption,

- Received a Gaussian distribution can approximate signal energy distribution based on central limit theorem (CLT) at the FC. Then, maximization of EE is posed as a non-convex optimization problem, to find the CRs required for collaboration, that satisfies a given constraint on the probability of false alarm and detection,
- Two scenarios of the problem formulation to jointly optimize EE problem whereas preserving the accuracy of detection to achieve maximum average throughput with the lower complexity analysis is then considered. Besides, a new energy-efficient scenario is considered in this paper to set the requirements of the minimum data rate for SUs to assure the quality of service (QoS). They formulated the maximization problem of mean EE for SUs despite preserving the accuracy of detection by jointly maximizing the perception time and SUs numbers that were subjected to the constraint of data rate, by applying non-linear fractional programming,
- We further address the issue of non-convexity optimization problem based on fractional programming and the Dinkelbach method. For this purpose, the optimization problem will transform into a similar concave problem. Then, iterative energy-efficient power allocation is elaborated to acquire the SUs optimal power transmission policy. Finally, great results to compare the developed EE soft decision fusion strategy is presented to analyze our scheme. Obviously, it is exhibited that our scheme outperforms recently presented schemes and improves the performance of the network.

C. ORGANIZATION

The remainder of this work is organized as follows. In Section II, system model details with cooperative sensing energy detection have been given, and Sec. III presents the global decision and local sensing system performance. Section IV describes the optimization problem formulation scheme for maximizing the EE perspective. In section VII, some results to validate the efficiency of our solution outperforms recently efficient scheme with discussions through simulations are presented. Finally, Sec. VIII provides the conclusion. In addition to this, a list of commonly used variables and special functions is provided in Table 1.

Notations: Throughout this paper, lightface symbols denote scalars, while boldface symbols represent matrices and vectors. The sets of real and complex numbers are denoted by $\mathbb{R}$, $\mathbb{C}$. $\mathcal{CN}\left(0, \sigma^2\right)$ denotes the complex Gaussian distribution with zero mean and variance σ^2. $[.]^H$ denotes the Hermitian transposition and $[.]^T$ represent the transposition of a vector or matrix; $\mathbb{E}\left(.\right)$ and $\mathbb{V}ar\left(.\right)$ represent the statistical expectation operator and the variance operator.

TABLE 1. List of notations.

Symbols	Definition
C	Licensed channel
N	Number of SUs in the network
B	Bandwidth
$y_i\left(n\right)$	Received signal at CR$_i$
$E_i\left(y\right)$	CR$_i$ average energy
CR$_i$	A given i^{th} cognitive radio
FC	Fusion center
τ_s	Sensing phase
τ_t	Transmission phase
T	Time frame length
λ_s	Global decision threshold
M	Number of samples
f_i^s	Sampling frequency of SU i
w_{ij}	Weight factor of CR$_i$ and j^{th} channel
H_0	Noise-only hypothesis testing
H_1	Signal-plus-noise hypothesis testing
P_f	Probability of false alarm
P_d	Probability of detection
$P\left(H_0\right)$	Probability of PU being absent
$P\left(H_1\right)$	Probability of PU being present
P_{max}	Maximum transmission power
$\hat{R}_{min}$	Minimum data rate
p_{ij}	Transmission power of SU i on channel j
γ	Average SNR
$\mathcal{L}\left(.\right)$	Lagrange function
$Q\left(.\right)$	Standard normal distribution tail probability
$\lVert.\rVert$	Frobenius norm
μ, ν	Lagrange multipliers
s	Non-negative step size
k	Iteration index

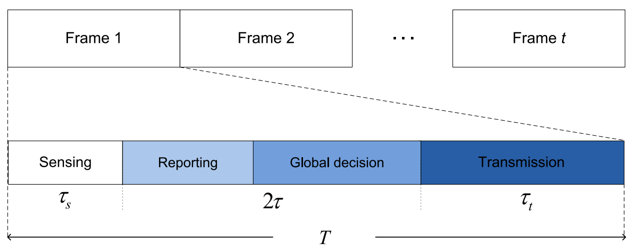

FIGURE 1. Periodic sensing time frame structure.

II. SYSTEM MODEL

A CR network with a single-hop infrastructure as well as N SUs, C licensed channels, and one FC assumed in a B Hz bandwidth permitted channel and control channel. The time period is also partitioned into frames, and all nodes synchronized with the FC. Frame designing is performed in such a way that every single of them is capable of sensing the CR by taking advantage of the periodic sensing model. The three phases of constructing the frame structure as in Fig. 1 are: a sensing phase, a reporting phase, and a transmission phase. Spectrum sensing is performed by all cooperative SUs by means of energy detection inside of the sensing phase. In the reporting phase, the local sensing data at each node is reported to the FC in the form of a power-encoded symbols sequence. The FC then makes a global decision based on the results of the local measurement received according to the identified threshold and disseminates the global decision through the control channel at the end of the reporting phase. The CR communications select a narrow band unlicensed spectrum as the control channel, which is contention-free but may eliminate the flat-fading process. The time of fusion and decision in FC is specified, and we set the time as a unit of time (mini-slot) for simplicity. Meanwhile, the transmission phase is slotted. The TDMA-MAC protocol plans transmissions in the transmission phase if the PUs are detected absent at the end of the reporting phase. At the beginning of the transmission phase, the data transmission is specifically centrally performed and broadcast by the FC over the control channel. After retrieving the schedule, each node transmits its data to the FC in the allocated time slot and falls asleep for the rest of the time. Specifically, the lengths of the sensing and transmission phases are represented by τ_s and τ_t, respectively, and the reporting phase one mini-slot length is denoted by τ. The length of a single frame is therefore given by $T = \tau_s + 2\tau + \tau_t$. PUs may be inactive during the sensing time but later become active during the transmission time. However, due to the low utilization of the PUs spectrum and the short duration of periodic sensing, the probability of this event will be negligible. To make the analysis tractable as well as to address the intrinsic feature of the considered problem, we assumed that the PUs status would be fixed within one frame.

A. SENSING

The measurement of local sensing per i^{th} user, $(1 \leq i \leq N)$, in a form of binary hypothesis for all $n = 1, 2, \ldots, M_i$ is,

$$y_i(n) = \begin{cases} \mathrm{w}_i(n), & H_0 \\ h_i(n)\, s(n) + \mathrm{w}_i(n), & H_1 \end{cases} \tag{1}$$

where H_0 and H_1 represents primary signal status (absence and presence), and $M_i = \tau_s f_i^s$ is the total number of samples with f_i^s as sampling frequency of SU_i. The primary signal is also denoted by $s(n)$. Furthermore, the noise of $\mathrm{w}_i(n) \sim \mathcal{CN}(0, \sigma_{\mathrm{w}})$ is taken to be a circular symmetric complex Gaussian noise. The channel gain $|h_i(n)|$ is assumed to be a Rayleigh distribution with the same variance of σ_h^2. Assuming $s(n)$, $\mathrm{w}_i(n)$, and $h_i(n)$ are independent of each other, the average signal-to-noise ratio (SNR) at each node can be obtained by $\gamma \triangleq \frac{\sigma_h^2 \sigma_s^2}{\sigma_{\mathrm{w}}^2}$ where σ_s^2 is the received fading PU signal variance. $E_i(y) = \frac{1}{M} \sum_{n=1}^{M_i} |y(n)|^2$ denotes the calculated average energy of the CR node i^{th} over M samples' detection interval as the test statistic for energy detector. However, the overall test statistics at the FC is as follows:

$$T_s^{all}(y) = \frac{1}{N} \sum_{i=1}^{N} E_i(y). \tag{2}$$

B. REPORTING

Generally, to compute $T_s^{all}(y)$, FC should collect $E_i(y)$ from CRs successively to express the local statistic of i^{th} SU. In conventional schemes, it is observed that the $E_i(y)$ transmission and computation of $T_s^{all}(y)$ are separated in the time domain. Computation schemes which are separation-based are often incompetent since computing $T_s^{all}(y)$ is not dependent on total reproduction of individual $E_i(y)$ at the FC. On the other hand, this work exploits the CoMAC scheme to promote the merging of transmitting and computing $T_s^{all}(y)$, as it only takes one time reporting phase unit (see Fig. 2). CR_i broadcast a sequence of complex and distinct symbolic values with the power of transmission that involves the $E_i(y)$ value. Specifically, the i^{th} transmission power is $P_i(E_i(y)) = \alpha_{arit}(E_i(y) - x_{min})$, if we define $\alpha_{arit} = \frac{P_{max}}{x_{max} - x_{min}}$, wherein P_{max} shows the SUs transmission power and $[x_{min}, x_{max}]$ $(x_{min} < x_{max})$ denotes the *sensing range*. $\mathbf{S}_i := [S_i[1], S_i[2], \ldots, S_i[L]]^T \in \mathbb{C}^L$ indicates a random transmission symbol sequence independently produced by the i^{th} SU and L represents the symbol sequence length. The sequence of SU i is denoted by $S_i[m] = \exp(\mathbf{i}\theta_i[m])$ $(m = 1, \ldots, L)$ where $\mathbf{i}$ is the imaginary part and $\{\theta_i[m]\}_{i,m}$ are independent identically and uniformly distributed continuous randomized phases on $[0, 2\pi)$. This implies $\|\mathbf{S}_i\|_2^2 = L$ and a constant envelope of the transmit signal (i.e., $|S_i[m]|^2 = 1$, for all m, i), which is a vital practical constraint.

Remark 1: Employing sequences with random phases and the constant envelope can outperform optimizing the sequences assigned to different nodes to decrease the overhead for coordination and to enhance scalability in comparison to systems that have optimized sequences. It is noteworthy that a corresponding sequence model may differ from a design for traditional asynchronous code division multiple access (CDMA) systems [20], which aim to obviate or lower the mutual interference. Contrarily, CoMAC schemes have to take advantage of the interference to reach a common objective, to calculate functions of sensor readings.

We propose that if it is possible to eliminate the effect of the fading channel from the receiver-side, each transmitter inverts its own channel to counteract this impact. CSI is necessary at each transmitter to achieve this goal. The known pilot signal transmitted by the FC can estimate the CSI. The pilot signal in practical systems can also help wake up sensor nodes and the computational process to initiate. Thus, the m^{th} transmit symbol of CR_i with the CSI at the nodes inverts its channel by sending [21]

$$\Gamma_i[m] = \frac{\sqrt{P_i(E_i(y))}}{|\tilde{h}_i(m)|} S_i[m], \tag{3}$$

where $|\tilde{h}_i(m)|$ shows independent complex-valued flat fading channel magnitude among the SU i and FC.[1] The channel magnitude $\left|\tilde{h}_i(m)\right|$ appears to be adequate for obtaining the same operation with full CSI link at the transmitter. Simultaneous transmission of SUs produces an output at the FC as

[1] The division by the channel amplitude is adequate so that the estimation of the channel phase is not required.

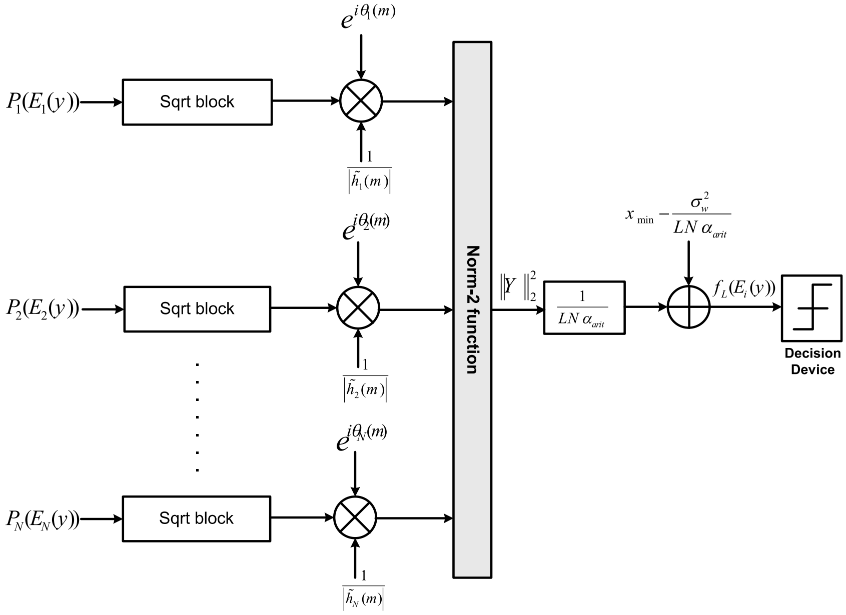

FIGURE 2. Block diagram of the CoMAC computation of user *N*.

follows [11],

$$\mathbf{Y} = \sum_{i=1}^{N} \sqrt{P_i\left(E_i\left(y\right)\right)}\mathbf{S}_i + \mathbf{W} \tag{4}$$

where $\mathbf{Y} := \left[Y\left[1\right], Y\left[2\right], \ldots, Y\left[L\right]\right]^T \in \mathbb{C}^L$ and $\mathbf{W} := \left[W\left[1\right], W\left[2\right], \ldots, W\left[L\right]\right]^T \in \mathbb{C}^L$ shows an independent stationary complex Gaussian noise vector with $\mathbf{W} \sim \mathcal{CN}\left(\mathbf{0}, \sigma_{\mathrm{w}}^2\mathbf{I}_L\right)$. By estimating the signal energy of (4) at $\|\mathbf{Y}\|_2^2$, the FC calculates an unbiased and *consistent* of the overall test statistic $T_s^{all}\left(y\right)$ estimation as $\hat{f}_L\left(\mathbf{E}\left(y\right)\right)$ where $\mathbf{E}\left(y\right) = \left[E_1\left(y\right), E_2\left(y\right), \ldots, E_N\left(y\right)\right]$. Specifically, let f be the desired function *arithmetic mean*,[2] then, the estimate $\hat{f}_L\left(\mathbf{E}\left(y\right)\right)$ of $f\left(\mathbf{E}\left(y\right)\right)$ is defined to be [21]

$$\hat{f}_L\left(\mathbf{E}\left(y\right)\right) := \frac{1}{N\alpha_{arit}}\left(\frac{\|\mathbf{Y}\|_2^2}{L} - \sigma_{\mathrm{w}}^2\right) + x_{min}. \tag{6}$$

All parameters in (6) are assumed to be known to the FC, where α_{arit}, L, and x_{min} are reported by the SUs and σ_{w}^2 can be obtained based on the long-term historical observation at the FC. To perform the energy detection, $\hat{f}_L\left(\mathbf{E}\left(y\right)\right)$ is exploited instead of T_s^{all}. According to (3), T_s^{all} is more informative for the FC to make the global decision.

[2]In mathematics, the sum of a collection of numbers divided by the count of numbers in the set (or group) as an arithmetic mean or a clear field merely as an average or the mean. Usually, the group is a set of results of an experiment or an empirical study, or often a set of values of assessment. Some contexts in mathematics and statistics choose "arithmetic mean" as a term to show its difference from other means, e.g., the geometric mean and the harmonic mean. In a data set, central tendency mean is an arithmetic measure, which is the easiest to understand and has the most applications. A measure of central tendency in statistics defines the term average. The arithmetic mean of a set of observed data is equal to the total of the numerical values of all of the observations divided by their total numbers. Considering the data set with the values of $\mathbf{E}\left(y\right)$, we can take into account the symbolic formula of the desired arithmetic mean f:

$$f\left(\mathbf{E}\left(y\right)\right) = \frac{1}{N}\sum_{i=1}^{N} E_i\left(y\right) = \frac{E_1\left(y\right), E_2\left(y\right), \ldots, E_N\left(y\right)}{N}. \tag{5}$$

III. DECISION PERFORMANCE ANALYSIS

For the final decision, $\hat{f}_L\left(\mathbf{E}\left(y\right)\right)$ is compared to the threshold value of λ_s by FC while the absence of the PU is estimated, if $\hat{f}_L\left(\mathbf{E}\left(y\right)\right) < \lambda_s$. However, the probabilities of false alarm and detection can be respectively expressed as

$$P_f = P\left(\hat{f}_L\left(\mathbf{E}\left(y\right)\right) \geq \lambda_s | H_0\right), \tag{7}$$

and

$$P_d = P\left(\hat{f}_L\left(\mathbf{E}\left(y\right)\right) \geq \lambda_s | H_1\right), \tag{8}$$

where the detection condition of Eqs. (7), (8) can be modified as follows:

$$\hat{f}_L\left(\mathbf{E}\left(y\right)\right) \geq \lambda_s \Longleftrightarrow \|\mathbf{Y}\|_2^2 \geq \eta\left(\lambda_s; L, N\right), \tag{9}$$

where $\eta\left(\lambda_s; L, N\right) = LN\alpha_{arit}\left(\lambda_s - x_{min}\right) + L\sigma_{\mathrm{w}}^2$.

A. SENSING PERFORMANCE APPROXIMATION

Given the importance of the total energy of vector $\mathbf{Y}$ for $\hat{f}_L\left(\mathbf{E}\left(y\right)\right)$, we first declare $\|\mathbf{Y}\|_2^2$ as follows

$$\|\mathbf{Y}\|_2^2 = \Delta_1 + \Delta_2, \tag{10}$$

where $\Delta_1 = L\sum_{i=1}^{N} P_i\left(E_i\left(y\right)\right)$ and $\Delta_2 = \mathbf{W}^H\mathbf{W} + \sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N} \sqrt{P_i\left(E_i\left(y\right)\right)P_j\left(E_j\left(y\right)\right)}\mathbf{S}_i^H\mathbf{S}_j + 2\sum_{i=1}^{N}\sqrt{P_i\left(E_i\left(y\right)\right)}\,\Re\left\{\mathbf{S}_i^H\mathbf{W}\right\}$. Obviously, Δ_1 is a linear combination of all

$\{E_i(y)\}_{i=1}^{N}$. The mean and variance conditions of $E_i(y)$ are

$$\mathbb{E}\{E_i(y)\} = \begin{cases} \sigma_w^2, & H_0 \\ (\gamma+1)\sigma_w^2, & H_1 \end{cases} \tag{11}$$

and

$$\mathbb{V}ar\{E_i(y)\} = \begin{cases} \frac{\sigma_w^4}{M_i}, & H_0 \\ \frac{(2\gamma+1)\sigma_w^4}{M_i}, & H_1 \end{cases} \tag{12}$$

However, the mean and variance of Δ_1 are

$$\mathbb{E}\{\Delta_1\} = L\sum_{i=1}^{N}\mathbb{E}\{P_i(E_i(y))\} = \begin{cases} L\Omega_0, & H_0 \\ L\Omega_1, & H_1 \end{cases} \tag{13}$$

and

$$\begin{aligned}\mathbb{V}ar\{\Delta_1\} &= L^2\sum_{i=1}^{N}\mathbb{V}ar\{P_i(E_i(y))\} \\ &= \begin{cases} \frac{L^2N\alpha_{arit}^2\sigma_w^4}{M}, & H_0 \\ \frac{L^2N\alpha_{arit}^2\sigma_w^4(2\gamma+1)}{M}, & H_1 \end{cases}\end{aligned} \tag{14}$$

where $\Omega_0 := N\alpha_{arit}\left(\sigma_w^2 - x_{min}\right)$ and $\Omega_1 := N\alpha_{arit}\left((\gamma+1)\sigma_w^2 - x_{min}\right)$. Similarly, the mean and variance of Δ_2 are:

$$\mathbb{E}\{\Delta_2\} = L\sigma_w^2, \tag{15}$$

and

$$\begin{aligned}\mathbb{V}ar\{\Delta_2\} &= L\sum_{i=1}^{N}\sum_{j\neq i}^{N}\sqrt{\mathbb{E}\left\{P_i(E_i(y))P_j\left(E_j(y)\right)\right\}} + L\sigma_w^4 \\ &\quad + 2L\sigma_w^2\sum_{i=1}^{N}\mathbb{E}\{P_i(E_i(y))\} \\ &= \begin{cases} L\Omega_0\left(N-1+2\sigma_w^2\right), & H_0 \\ L\Omega_1\left(N-1+2\sigma_w^2\right) + L\sigma_w^4, & H_1 \end{cases}\end{aligned} \tag{16}$$

However, we are ready to derive the mean and variance of $\|\mathbf{Y}\|_2^2$ by assuming $\mathbf{S}_i$ and $\mathbf{W}$ are mutually independent as below,

$$\mathbb{E}\left\{\|\mathbf{Y}\|_2^2\right\} = \begin{cases} L\left(\Omega_0+\sigma_w^2\right), & H_0 \\ L\left(\Omega_1+\sigma_w^2\right), & H_1 \end{cases} \tag{17}$$

and

$$\mathbb{V}ar\left\{\|\mathbf{Y}\|_2^2\right\} = \begin{cases} L\Omega_0\left(N-1+2\sigma_w^2\right) + \frac{L^2N\alpha_{arit}^2\sigma_w^4}{M}, & H_0 \\ L\Omega_1\left(N-1+2\sigma_w^2\right) + L\sigma_w^4 \\ \quad + \frac{L^2N\alpha_{arit}^2\sigma_w^4(2\gamma+1)}{M}, & H_1 \end{cases} \tag{18}$$

Due to the complexity of the expression $\|\mathbf{Y}\|_2^2$, its exact distribution will be unavailable even if the mean and variance are known. However, we can approximate $\|\mathbf{Y}\|_2^2$, with the aid of CLT [22], based on Gaussian distribution. Hence, for a sufficiently large L, false alarm probability can be approximated as follows:

$$\begin{aligned} P_f &= P\left(\|\mathbf{Y}\|_2^2 \geq \eta(\lambda_s; L, N)\,|H_0\right) \\ &= Q\left(\frac{LN\alpha_{arit}\left(\lambda_s-\sigma_w^2\right)}{\sqrt{L\Omega_0\left(N-1+2\sigma_w^2\right)+\frac{L^2N\sigma_w^2\alpha_{arit}^2}{M}}}\right), \end{aligned} \tag{19}$$

Next, the global probability of detection can be simplified as follow:

$$\begin{aligned} P_d &= P\left(\|\mathbf{Y}\|_2^2 \geq \eta(\lambda_s; L, N)\,|H_1\right) \\ &= Q\left(\frac{LN\alpha_{arit}\left(\lambda_s-(1+\gamma)\sigma_w^2\right)}{\sqrt{L\Omega_1\left(N-1+2\sigma_w^2\right)+L\sigma_w^4+\frac{L^2N\alpha_{arit}^2\sigma_w^4(2\gamma+1)}{M}}}\right), \end{aligned} \tag{20}$$

where $Q(.)$ is complementary cumulative distribution function (CCDF), which calculates the tail probability of a zero mean unit variance Gaussian variable; that is, $Q(x) = \int_x^{+\infty}\exp\left(-t^2/2\right)dt/\sqrt{2\pi}$. From (19) and (20), we have to constrain λ_s to make $P_d > 0.5$ and $P_f < 0.5$, which ought to be the most CR scenarios case.

IV. OPTIMIZATION PROBLEM FORMULATION

Here, the fundamental tradeoff of sensing capability and available throughput corresponding to the secondary networks is investigated. By using an energy detection scheme, one can obtain the maximum throughput for an optimum sensing time, and protecting the PUs adequately. In this section, we elaborate on the data transmission, energy consumption, and EE models in detail. The optimization problem aims at maximizing the EE of the optimum sensing to determine the optimum detection threshold and the time in a way that energy consumption reaches the lowest value as the EE reaches the highest value. Considering C_0 as the secondary network throughput provided in PUs absence and C_1 as the throughput of the PUs presence, obviously, $C_0 > C_1$. It is worth mentioning that the formula, as discussed above for C_1, could be considered as a lower bound of the secondary link accessible rate whenever the PU is active provided that the signal of the PU is non-Gaussian. Defining $P(H_0)$ and $P(H_1)$ as the PU absence and presence probabilities, $P(H_0) + P(H_1)$ is equal to 1 for a certain frequency band of interest. We assume that the i^{th} SU is allotted a segment of the j^{th} channel that can be accomplished through either filter bank multicarrier (FBMC)[3] or orthogonal frequency

[3] Multicarrier modulation with a long track history in wireless communications is considered widespread practical applications in the form of orthogonal frequency division multiplexing (OFDM) channels, with advances in integrated circuits. Long term evolution (LTE), Wi-Fi, and digital video broadcasting-terrestrial (DVB-T) are the current applications of OFDM technology. Orthogonal pulses overlap in time and frequency transmit the information in multicarrier systems. These pulses are highly preferable as they cover small bandwidth, thus transforming frequency-selective broadband channels, with negligible interference, into multiple, virtually frequency flat, sub-channels.

division multiple access (OFDMA), at a transmission power of p_{ij}. Consequently, two scenarios can be viewed, meaning the secondary networks can keep running at the frequency band of the PU. Future portable systems will be described by enormous scope provided by conceivable uses, from enhanced mobile broadband over enhanced machine-type communications to ultra-reliable low latency communications [23], [24]. A high subcarrier is dispersing pass the low latency transmissions, while small subcarrier spacing raises the bandwidth efficiency. Besides, extraordinary subcarrier spacing facilitates matching the transmission framework to specific channel conditions. A user at high velocities should utilize a high subcarrier dispersing. If multipath delay spread is the limiting factor, small subcarrier spacing would be the better choice. Other calculations presented lower delay spreads [25]. The little delay spread is the indicator of the adequacy of low-complexity one-tap equalizers to achieve an operational optimum in FBMC. Rayleigh fading is mainly observed by relocating the receive antennas inside a couple of wavelengths but not over the frequency domain.

S1. There are no PUs and SU does not make false alarm. In this scenario, the energy consumed, $\hat{E}_1$, and the achievable secondary link throughput are explored by $N\left(E_s\tau_s + LE_t v\right) + \left(T - 2\tau - \tau_s\right)E_t$ and $\frac{T-2\tau-\tau_s}{T}C_0$, where E_s, E_t, and v represents the sensing power, transmission power, and symbol duration, respectively.

S2. In this scenario, secondary link achievable throughput and energy consumed of $\hat{E}_2$ corresponding to the secondary link is determined by $\frac{T-2\tau-\tau_s}{T}C_1$ and $\hat{E}_1 = \hat{E}_2$, respectively, the latter is the same as the **S1**.

In this case, the achievable transmission rate of SU is

$$G_{ij} = Bw_{ij}\log_2\left(1 + \frac{p_{ij}h_{ij}}{w_{ij}\sigma_s^2}\right), \tag{21}$$

where $w_{ij} \geq 0$ is the weighting factor of CR_i and the j^{th} channel, and h_{ij} is the channel coefficient of i^{th} user on channel j. We assume $\sum_{i=1}^{N} w_{ij} = 1, j \in \mathbf{C}$ without loss of generality. Hereafter, the probabilities of **S1** and **S2** are respectively $\left(1 - P_f\right)P\left(H_0\right)$ and $\left(1 - P_d\right)P\left(H_1\right)$. If we define

$$\hat{R}_0 = \frac{T - 2\tau - \tau_s}{T}\sum_{i=1}^{N}\sum_{j=1}^{C}\left[C_0\left(P\left(H_0\right)\left(1 - P_f\right)\right)\right]G_{ij}, \tag{22}$$

and

$$\hat{R}_1 = \frac{T - 2\tau - \tau_s}{T}\sum_{i=1}^{N}\sum_{j=1}^{C}\left[C_1\left(P\left(H_1\right)\left(1 - P_d\right)\right)\right]G_{ij}. \tag{23}$$

To ensure the sensing accuracy, probability of detection lower limit can be fixed precedently, and the average throughput maximization problem is conceived as equation (24) (as shown at the bottom of the next page) where $\mathbf{C} = \{1, 2, \ldots, C\}$, $\mathbf{N} = \{1, 2, \ldots, N\}$, and $\mathbf{p}$ denotes the vector of p_{ij}. Also, $\bar{P}_d$ is the lower limit of detection probability that requires to achieve the protection of PU, $\bar{P}_f$ exploits the false alarm probability upper limit, and P_{max} is the SUs maximal transmission power. Apparently for the specified time frame T, the more sensitive time τ_s and the reporting time τ, the data transfer available time of $(T - 2\tau - \tau_s)$ seems to be shorter. Generally, the false alarm and detection probabilities mainly depend on the local sensing duration and the number of cooperative users N. Actually, the increase of τ_s and N leads to a higher detection probability and a lower false alarm probability, which implies a better sensing capability, but also means less time and power for the later data transmission. Thus, there is a tradeoff between cooperative spectrum sensing and throughput. Alternatively, $Q(x)$ is a function of x for specified probability of detection (P_d) that decreases monotonically. Therefore, the probability of false alarm is concurrent with a longer sensing time, which is consistent with the fact that the secondary network can utilize the channel within a higher chance manner. However, sensing throughput tradeoff aims to establish the desired length of each frame while protecting the PUs, can achieve the maximum attainable secondary networks throughput. A preferable problem optimization objective function, concerning EE, should be able to calculate the number of bits which one Joule of the consumed energy can allow to transmit [26]. A high SNR level necessitates more power, which can cause a bit error rate (BER) to decrease and throughput to increase. A high power, nevertheless, implies lower battery life in terminals, in addition to being harmful to the environment. Data transmission is an enormous energy-consumer and necessitates to develop strategies for energy-efficient data transmission to decrease power usage and extend the CR lifetime. Contrarily, the transmission performance should be guaranteed while minimizing power consumption is crucial. Hence, EE performance can also be specified as the average throughput and average energy consumption over a period of time, containing sensing and transmission power. Therefore, the EE (bits/sec/Hz/Joule) can be written as below,

$$\hat{\xi}\left(\tau_s, \lambda_s, L, \mathbf{p}\right) = \frac{\hat{R}_s\left(\tau_s, \lambda_s, L, \mathbf{p}\right)}{\hat{E}\left(\tau_s, \lambda_s, L\right)}. \tag{25}$$

Accordingly, using the energy consumed in **S1** and **S2**, one can estimate the average energy consumption for data transmission within a frame as follows,

$$\begin{aligned}\hat{E}\left(\tau_s, \lambda_s, L\right) &= \hat{E}_1 + \hat{E}_2 \\ &= N\left(E_s\tau_s + LE_t v\right) \\ &\quad + \left(T - 2\tau - \tau_s\right)E_t(P\left(H_0\right)\left(1 - P_f\right) \\ &\quad + P\left(H_1\right)\left(1 - P_d\right)).\end{aligned} \tag{26}$$

In similar fashion, it is assumed that $P\left(H_1\right) < 0.5$ as described in [27]. Since EE includes sensing accuracy, total energy consumption, and achievable throughput, this comprehensive metric is extensively utilized to indicate the overall performance of a system. By decreasing the average energy consumed per frame, (25) is substantially increased; however, one can find a principal method to have green CRs' EE increased. Given an effective coefficient $(0 < \alpha < 1)$

constraint, (25) can be considered as:

$$\begin{aligned}
&\min_{\tau_s,\lambda_s,L} \hat{E}(\tau_s,\lambda_s,L)\\
&\text{subject to: } \hat{E}_i(\tau_s,\lambda_s,L)\geq 0,\\
&\qquad \tau_{min}\leq\tau_s\leq T-2\tau,\\
&\qquad L_{lower}\leq L\leq L_{max},\\
&\qquad f_\alpha(\tau_s)=\alpha\hat{E}(\tau_s),\\
&\qquad \hat{E}(\tau_s):=\hat{E}(\tau_s,\lambda_s,L). \qquad (27)
\end{aligned}$$

Under the primary communication protection condition, the aim is to optimize the mean EE, whereas preserving the accuracy of detection by maximizing the sensing time duration and SUs subject to the average transmit power constraints and the average sustainable power for PUs. In CR networks, energy is consumed during different spectrum management activities such as data reporting and spectrum sensing. When designing spectrum decision schemes, considering energy efficient methods to ensure the less energy consumed during cognitive activities should be mentioned. According to CR reconfiguration[4] framework, an intelligent choice can lead to lower power and energy consumption. In the medium- and long-range wireless communications, power amplifier usually dominates power and energy consumption. Based on the mentioned points, the CR-EE comparison could be found in Table 2. Herein, the EE maximization problem for a given predefined threshold Λ (that is close to but less than 1) can be reformed as below,

$$\begin{aligned}
&\mathbf{P1}: \max_{\tau_s,\lambda_s,L,\mathbf{p}} \hat{\xi}(\tau_s,\lambda_s,L,\mathbf{p})=\frac{\hat{R}_s(\tau_s,\lambda_s,L,\mathbf{p})}{\hat{E}(\tau_s,\lambda_s,L)}\\
&\text{subject to: } P_d(\tau_s,\lambda_s,L)\geq\Lambda,\\
&\qquad 0\leq\tau_s\leq T-2\tau,\\
&\qquad \lambda_s\geq 0,\\
&\qquad L_{lower}\leq L\leq L_{max},\\
&\qquad \sum_{i=1}^{N} w_{ij},\ j\in\mathbf{C},\\
&\qquad 0\leq w_{ij}\leq 1,\ i\in\mathbf{N},\quad j\in\mathbf{C},\\
&\qquad \sum_{j=1}^{C} p_{ij}\leq P_{max},\ i=1,\ldots,N,\\
&\qquad p_{ij}\geq 0,\ i\in\mathbf{N},\quad j\in\mathbf{C}. \qquad (28)
\end{aligned}$$

where L_{lower} and L_{max} respectively represent the lower and upper bounds of L. The exploited optimization problem of (28) is considered as a non-convex problem. To deal with this problem, we turn it to a convex one through nonlinear fractional and sequential convex programming in the following sections.

Theorem 1: Given that each local maximum in (28) *is known as a global maximum that has one maximum,* **P1** *is considered to be completely quasi-concave.*

It has been shown that the numerator and denominator of the optimization objective (25) of the original problem **P1** in (28) are concave and affine **p**, respectively. The objective function (25) is a pseudo-concave function. Accordingly, **P1** is a non-linear fractional program (we present our detailed approach by the following section).

[4]In traditional wireless networks, radio terminals are set up to operate over pre-defined frequency channels with pre-defined transmitter parameters and specifications. Although such systems may use adaptive techniques to modify various parameters such as transmission power and modulation and coding schemes (MCS), their hardware-based architecture restricts their flexibility to conform to the external environment. However, the inaccessibility of the heterogeneous spectrum and DSA requires systems that are much more flexible. Therefore, CR networks provide such flexibility to quickly adjust their transceiver parameters (e.g., channel width, center frequency, transmission power, and MCS) upon external RF environment stimuli, policy updates, QoS requirements, selected spectrum, channel characteristics, and user's needs. This flexibility is easily achieved by performing CR using SDRs [3].

$$\begin{aligned}
&\max_{\tau_s,\lambda_s,L,\mathbf{p}} \hat{R}_s(\tau_s,\lambda_s,L,\mathbf{p})=\hat{R}_0+\hat{R}_1\\
&\quad=\left(\frac{T-2\tau-\tau_s}{T}\right)\sum_{i=1}^{N}\sum_{j=1}^{C}\left[\left(C_0\left(P(H_0)\left(1-P_f\right)\right)+C_1\left(P(H_1)\left(1-P_d\right)\right)\right)G_{ij}\right]\\
&\text{subject to: } 0\leq\tau_s\leq T-2\tau,\\
&\qquad P_d\geq\bar{P}_d,\\
&\qquad P_f\leq\bar{P}_f,\\
&\qquad \sum_{i=1}^{N} w_{ij},\ j\in\mathbf{C},\\
&\qquad 0\leq w_{ij}\leq 1,\ i\in\mathbf{N},j\in\mathbf{C},\\
&\qquad \sum_{j=1}^{C} p_{ij}\leq P_{max},\ i=1,\ldots,N,\\
&\qquad p_{ij}\geq 0,\ i\in\mathbf{N},j\in\mathbf{C}. \qquad (24)
\end{aligned}$$

TABLE 2. EE solutions for CR technologies.

Reference	Use Case	Target	Framework
[29]	Energy-efficient CR techniques and green energy powered wireless networks optimization	Discussing the various aspects of green CR energy resources	Capture and save ambient energy for environmentally friendly production of fossil fuels, to generate energy form.
[30]	Optimization of EE with continuous spectrum sensing	EE optimization	Focusing EE optimization under the constraints of sensing performance with obtaining the optimal solution.
[31]	Energy-efficient CR based on multiband sensing and spectrum sharing	Obtaining optimal sensing via energy based scheme	Obtain the optimal spectrum sensing time and power allocation by using the energy consumption reduction and data transferring for SU systems.
[32]	On the optimization of SE and EE tradeoff for future networks	Increasing SE as well as EE to demonstrate the effectiveness of the sensing strategies	Considering SE-EE tradeoff for CR networks with cooperative sensing in the case of formulating the general optimization problem through analyzing the two special cases.
[33]	Energy-efficient QoS based route management	Energy based QoS optimization	Use of the profile exchanging functionalities and location services mechanism, including any features of PU exchanges and channels with a central entity.
[34]	Energy-efficient optimal sensing and transmission in CR networks	EE optimization	Considering the case of PU protection from user transmission in order to optimize EE via a sub-optimal ISA algorithm to maximize the efficiency by optimizing sensing time and transmission time.

A. DECOMPOSITION

For simplicity, we present the EE performance by q, i.e.,

$$q^* = \hat{\xi}^* = \frac{\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}^*)}{\hat{E}(\tau_s, \lambda_s, L)}. \tag{29}$$

Defining the function form of q to be

$$\begin{aligned} \mathbf{P2}: F(q) = &\max_{\mathbf{p}} \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q\hat{E}(\tau_s, \lambda_s, L), \\ &\text{subject to: } \sum_{j=1}^{C} p_{ij} \le P_{max}, \ \forall i \text{ and } p_{ij} \ge 0, \\ &i \in \mathbf{N}, j \in \mathbf{C}. \end{aligned} \tag{30}$$

We next show in Lemma 1 that $F(q)$ is a strictly decreasing function that is always non-negative.

Lemma 1: The function $F(q)$ is strictly decreasing for every feasible EE value and $F(q) \ge 0$.

Proof: The proof can be found in Appendix A. □

Based on Lemma 1, we present the following theorem to reformulate the optimization problem into a friendly form.

Theorem 2: The optimal EE of CR_i and optimal transmission $(\tau_s, \lambda_s, L, \mathbf{p}')$ are obtained if and only if $F(q^*) = F(q^*; \tau_s, \lambda_s, L, \mathbf{p}') = 0$ where $q^* = \hat{\xi}^* = \frac{\hat{R}_s(\tau_s,\lambda_s,L,\mathbf{p}^*)}{\hat{E}(\tau_s,\lambda_s,L)}$.

Proof: The proof is given in Appendix B. □

V. SOLUTION OF THE PROBLEM

Now, the optimization algorithm and *fractional programming* are applied to calculate the problem **P1**. Then, sensing and transmission power allocation are optimized simultaneously using the iterative Dinkelbach algorithm [34]. Then nonlinear fractional and parametric programming are used to compute objective function (24).

A. EQUIVALENT CONCAVE PROGRAMMING TRANSFORMATION AND KKT-BASED SUBOPTIMAL POWER ALLOCATION

The fractional programming obtained in (28) can be stated in the condition form of below [36],

$$\begin{aligned} &\max_{p \in \mathcal{P}} \frac{f(p)}{q(p)}, \\ &\text{subject to: } h_i(p) \le 0, i \in \mathbf{N}. \end{aligned} \tag{31}$$

In such follows, the properties of (31) can be expressed as a concave fractional program as follows: (i) the functions $f(p)$, $g(p)$, and $\{h_i(p)\}_{i=1}^{N}$ are all real values defined on the $\mathcal{P} \in \mathbb{R}^n$ set, (ii) $f(p)$ and $g(p)$ are concave and affine sign on $\mathcal{P}$, and (iii) if $g(p)$ is not affine, the set $f(p)$ on S is considered positive where $S = \{p \in \mathcal{P} : h_i(p) \le 0, i \in \mathbf{N}\}$. A concave fractional programming objective function is quasi-concave, and a global maximum in quasi-concave problem cannot be assured as the optimal solution. When $g(p)$ is severely convex or $f(p, z)$ is strictly concave, the concave fractional program has a maximum of one solution point [36], [37]. If g and S are convex and f is concave and non-negative, then (31) is claimed as a concave-convex fractional program that provides an efficient approach to calculate a limited fractional programming problems class. However, a concave fractional program can be converted to a concave problem, and any local maximum point can also be guaranteed as a global maximum point for a convex problem. Given the concavity of $\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p})$ based on the transmission power and the affine function of $\hat{E}(\tau_s, \lambda_s, L)$, **P1** would be the considered quasi-concave function. In a differentiable equivalent concave problem, an optimal solution is provided by a solution of *Karush-Kuhn-Tucker* (KKT) *conditions*. Then, Lagrangian duality theorem is used to calculate the suboptimization problem as shown in (32), at the bottom of the next page, where μ and ν are the non-negative Lagrangian multipliers. Also, $\hat{R}_{min}$ represents the minimum data rate demands by SUs. The optimization problem can be then transformed into a Lagrangian duality as,

$$\min_{\mu,\nu} \max_{\mathbf{p}} \mathcal{L}(\mu, \nu, \mathbf{p}),$$
$$\text{subject to: } \mu \geq 0, \nu \geq 0. \tag{33}$$

The power allocation subproblem exists in the optimization problem formulated in (33) and may have a repetition solution. The internal maximum subproblem can use a series of Lagrange multipliers to maintain the locally optimal power allocation. The Lagrange dual-decomposition method [38] can separate (33) to a number of subproblems parallel to each other in the same manner for [36]. These subproblems have the same structure for each fading state. The corresponding subproblem for a particular fading state can be therefore given as (34). Here, the external minimum subproblem of updated Lagrange multipliers can extract a resolving strategy afterward. where the external minimum subproblem of updated Lagrange multipliers can afterward obligate the strategy to find a solution. After substituting G_{ij} from (21) to (32), we can calculate the derivative of the Lagrange function and modification,

$$\frac{\partial \mathcal{L}(\mu, \nu, \mathbf{p})}{\partial \mathbf{p}} = -\mu C - \frac{BCNw_{ij}h_{ij}(T - 2\tau - \tau_s)\varrho_s}{\left(p_{ij}h_{ij} + w_{ij}\sigma_s^2\right)} \tag{35}$$

where

$$\varrho_s = \frac{\left(C_0\left(P_f - 1\right)P(H_0) + C_1(P_d - 1)P(H_1)\right)}{T\ln 2} \tag{36}$$

By setting $\frac{\partial \mathcal{L}(.)}{\partial \mathbf{p}} = 0$, we can find the optimal point for energy-efficient power allocation mechanism as follows:

$$\mathbf{p}^* = \left[-\frac{BNw_{ij}(T - 2\tau - \tau_s)\varrho_s}{\mu} - \frac{w_{ij}\sigma_s^2}{h_{ij}}\right]^+ \tag{37}$$

where $(a)^+ = \max(0, a)$.

B. PARAMETRIC OPTIMIZATION ITERATIVE SOLUTION

An iterative fractional programming technique based on less cumbersome Dinkelbach mathematical technique does not require the transformation. This algorithm first transforms the fractional programming objective to a parametric optimization problem, afterwards, ε-optimal arrangements are acquired iteratively by assuming ε as the convergence tolerance, i.e., $\varepsilon \in [\varepsilon_0, \varepsilon_1]$. Consider the following general optimization problem, where $p \in \mathbb{R}^n$ and $q \in \mathbb{R}$

$$\max_{p} \frac{K(p)}{D(p)},$$
$$\text{subject to: } p \in S. \tag{38}$$

The parametric problem associated with Equation (38) can be written as follows:

$$\max_{p} K(p) - qD(p),$$
$$\text{subject to: } p \in S. \tag{39}$$

There is one-to-one relation among the fractional and iterative concave programming solutions with the parametric objective as indicated in the following theorem:

Theorem 3: $q^* = \frac{K(p^*)}{D(p^*)} = \max_{p\in S} \frac{K(p)}{D(p)}$ if and only if, $\max_{p\in S} K(p) - q^*D(p) = K(p^*) - q^*D(p^*) = 0$.

To achieve power allocation, we convert our optimization problem into a similar one (12) and go on to propose a repetition of ε-optimal algorithm. We are therefore using fractional programming to transform **P1** to a convex one, reformulated

$$\begin{aligned}
\mathcal{L}(\mu, \nu, \mathbf{p}) &= \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q\hat{E}(\tau_s, \lambda_s, L) - \mu\left(\sum_{j=1}^{C} p_{ij} - P_{max}\right) - \nu\left(\hat{R}_s - \hat{R}_{min}\right) \\
&= \left(\frac{T - 2\tau - \tau_s}{T}\right)\sum_{i=1}^{N}\sum_{j=1}^{C}\left[\left(C_0\left(P(H_0)\left(1 - P_f\right)\right) + C_1\left(P(H_1)(1 - P_d)\right)\right)G_{ij}\right] \\
&\quad - qN(E_s\tau_s + LE_t\nu) + (T - 2\tau - \tau_s)E_t(P(H_0)\left(1 - P_f\right) + P(H_1)(1 - P_d)) \\
&\quad - \mu\left(\sum_{j=1}^{C} p_{ij} - P_{max}\right) - \nu\left(\hat{R}_s - \hat{R}_{min}\right) \\
\text{subject to: } &\sum_{j=1}^{C} p_{ij} \leq P_{max}, \\
&\hat{R}_s - \hat{R}_{min} \geq 0, \\
&p_{ij} \geq 0.
\end{aligned} \tag{32}$$

as **P2**. Algorithm 1 presents the pseudo-code of the iterative scheme. The iterative method-based EE maximization algorithm, which we proposed earlier, is, however, shown in Algorithm 1. We are now able to prove that the algorithm is convergent.

Algorithm 1 Iterative Method-Based EE Maximization Algorithm

Require: Initialize I_0, ε_0, $k = 0$, $q = 0$, and Convergence=false.
Ensure: $F(\mathbf{p}, q) = \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q\hat{E}(\tau_s, \lambda_s, L)$
  while (Convergence=false) and ($k \leq I_0$) **do**
    $\mathbf{p} \leftarrow \arg\max_{\mathbf{p}} \{F(\mathbf{p}, q) \,|\text{Eq.(28)}\}$
    if $F(\mathbf{p}, q) = 0$ **then**
      Convergence=true
      return $\mathbf{p}^* = \mathbf{p}$
    else if $F(\mathbf{p}, q) \leq \varepsilon_0$ **then**
      Convergence=true
      return $\mathbf{p}_{\varepsilon_0} = \mathbf{p}$
    else
      update, $q \leftarrow \frac{\hat{R}_s(\tau_s,\lambda_s,L,\mathbf{p})}{\hat{E}(\tau_s,\lambda_s,L)}$
      update, $k \leftarrow k + 1$
    end if
  end while

Lemma 2: $\exists q$ such that $F(q) = 0$.

Proof: The proof is deferred to Appendix C. □

Lemma 3: $F(q)$ is decreasing in q.

Proof: The proof is given by Appendix D. □

Theorem 4: The iterative algorithm will always converge to ε-optimal solution.

Proof: The proof can be found in Appendix E. □

We iteratively update μ and ν using a sub-gradient method in order to compute the external minimum subproblem in terms of the Lagrange multipliers as [36]-[40],

$$\mu(k+1) = \left[\mu(k) - s\left(\sum_{j=1}^{C} p_{ij} - P_{max}\right)\right]^+, \tag{40}$$

$$\nu(k+1) = \left[\nu(k) - s\left(\hat{R}_s - \hat{R}_{min}\right)\right]^+. \tag{41}$$

where k denotes the index iteration and s is the step size constant to converge to the optimal value. In each k, we first update μ and ν by $\mathbf{p}^*$, and then use optimal values of μ and ν in the subsequent iterations to obtain $\mathbf{p}^*$. The analysis of the KKT-based complexity approach can be found in Algorithm 2, which provides the searching duality Lagrangian power allocation procedure and can be applied in a straightforward model to solve the CR communications power allocation.

Algorithm 2 Lagrange KKT-Based Power Allocation Algorithm

Require: Initialize I_1, ε_1, Lagrangian multipliers $\mu(k)$ and $\nu(k)$ for $k = 0$, and Convergence=false.
  while (Convergence=false) and ($k \leq I_1$) **do**
    Compute $\mathbf{p}^*$ using (37).
    Update μ and ν by (40) and (41) using sub-gradient method:
    $\mu(k+1) = \left[\mu(k) - s\left(\sum_{j=1}^{C} p_{ij} - P_{max}\right)\right]^+$
    $\nu(k+1) = \left[\nu(k) - s\left(\hat{R}_s - \hat{R}_{min}\right)\right]^+$
    if $|\mu(k+1) - \mu(k)| + |\nu(k+1) - \nu(k)| \leq \varepsilon_1$ **then**
      The algorithm terminates,
      Convergence=true
      return $\mathbf{p}^* = \mathbf{p}$
    else
      update, $k \leftarrow k + 1$
    end if
  end while

TABLE 3. Parameter settings.

No.	Parameters	Values
1	Maximum power budget (P_{max})	20 W
2	Lower bound of L (L_{lower})	200
3	Upper bound of L (L_{max})	625
4	Sampling frequency (f_s)	6 MHz
5	Transmission power (E_t)	3 W
6	Symbol duration (υ)	16 μs
7	Mini-slot length (τ)	10 ms
8	Sensing power (E_s)	100 mW
9	Bandwidth (B)	3 MHz

VI. COMPLEXITY ANALYSIS

We now analyze the joint iterative power allocation subproblem mathematical computation complexity. Generally, regarding the fact that the iteration number necessary for Lagrange multipliers and the transmit power to reach convergence is rather small, the procedure is somehow straightforward and simple. Note that it is necessary to update dual variables of μ and ν for convergence. Hence, the fractional programming complexity and the sub-gradient searching method is $\mathcal{O}(NI_0I_1)$ by supposing I_0 and I_1 as the outer loop and the inner loop iteration numbers.

VII. SIMULATION RESULTS AND EVALUATIONS

Next, we present our framework with discussions to eliminate the performance taking in account of different key system parameters. The values of the parameters are given in Table 3, as in [27], [39]. The other parameters used in this simulation are $N = [10, 15, 20]$, $\alpha_{arit} = 10$, and

$$\max_{\mathbf{p}} y(\mathbf{p}) = \left(\frac{T - 2\tau - \tau_s}{T}\right) \sum_{i=1}^{N} \sum_{j=1}^{C} \left[\left(C_0\left(P(H_0)\left(1 - P_f\right)\right) + C_1\left(P(H_1)(1 - P_d)\right)\right) G_{ij}\right] - \mu \sum_{j=1}^{C} p_{ij} \tag{34}$$

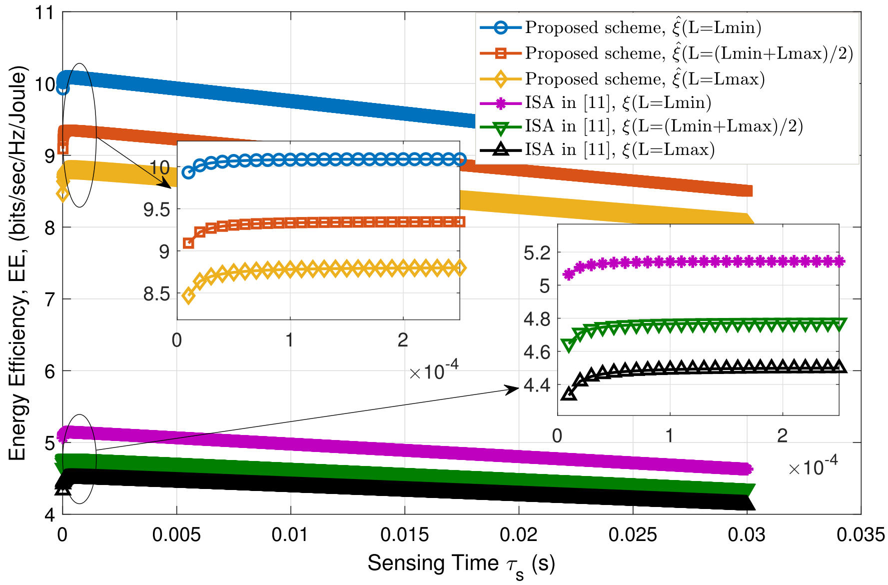

FIGURE 3. **Maximum EE comparison: γ=-16 dB for 10 users with fixed L.**

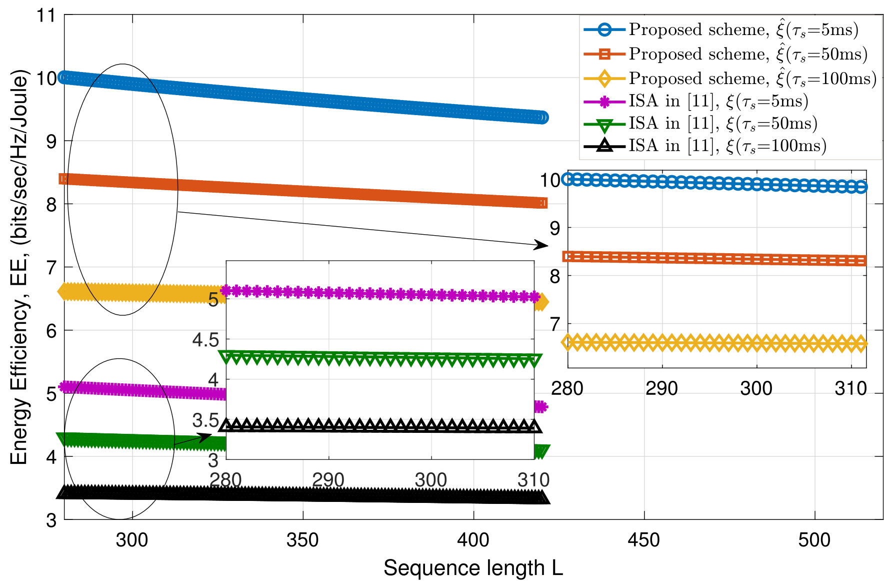

FIGURE 4. **Maximum EE comparison: γ=-16 dB for 10 users with fixed τ_s.**

$P(H_0) = 0.8$. However, transmission rate is adopted to be $C_0 = \log_2(1+\gamma_s) = 6.658$ bits/sec/Hz where γ_s considered as SNR and is 20 dB, and $C_1 = \log_2\left(1+\frac{\gamma_s}{1+\gamma_p}\right) = 6.613$ bits/sec/Hz by assuming $\gamma_p = -15$ dB. We also choose the frame duration $T = 300$ ms. Noise samples are appropriated to be Gaussian with zero mean and variance 1. For comparison, we take the scheme in [11] as a reference. In Fig. 3, the proposed scheme compared to ISA algorithm shows the EE maximization against the sequence length. In particular, with a significant reduction in the energy consumption based on our results, we arrive at an increase in the EE with the same sensing time of 2.5 ms for different values of (λ_s, L) and $L = \left\{L_{min}, \frac{L_{min}+L_{max}}{2}, L_{max}\right\}$. Thus, the EE maximization of this form is twice approximately, making way for the next-generation green communications network. Figure 4 presents the EE maximization with the same symbol sequence length of $L_{min} = 280$ for (λ_s, L) and different values of $\tau_s = \{5\,\text{ms}, 50\,\text{ms}, \text{and } 100\,\text{ms}\}$. As shown in this figure, EE is maximized by decreasing the sensing phase length in comparison with ISA algorithm. In this form, considering the energy consumption, it is possible to increase the EE by approximately 70% in the proposed method. Compare to Fig. 3 with 4, we can discover that for each rule, the EEs obtained are always higher than the others. It is because compared to

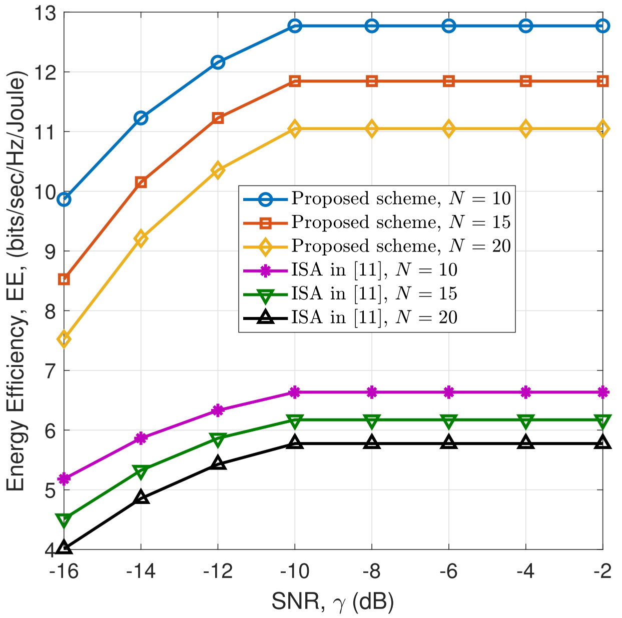

FIGURE 5. **Comparison of maximum EE for various SNRs and users.**

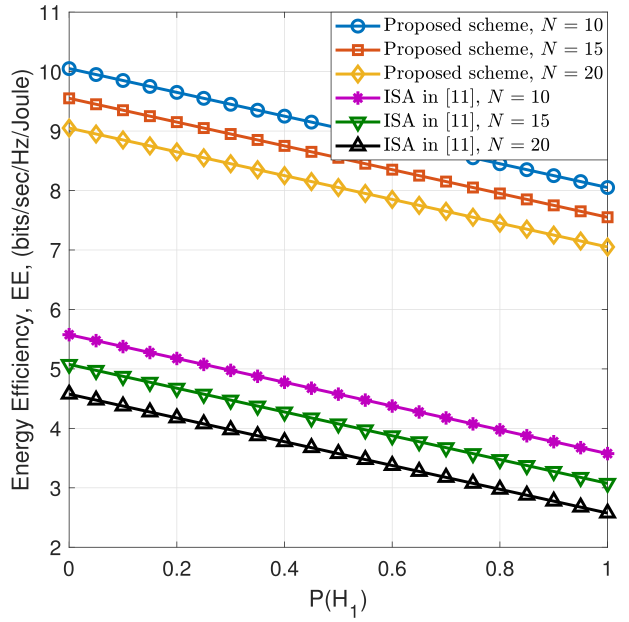

FIGURE 6. **Comparison of maximum EE for various $P(H_1)$ and three users group.**

power transmission constraints, conventional ISA is looser, and our method with its power allocation is more flexible. However, more power can be allocated by the transmitter under the good channel constraints.

However, the EE maximization of this work compared to [11] for various users and SNRs from -16 to -2 dB is depicted in Fig. 5, respectively. Concerning traditional cooperative sensing, individual users local statistic has to be transmitted to the FC in different time intervals. Consequently, the reporting delay in the reporting phase of traditional cooperative spectrum sensing rises linearly with N. More interestingly, EE is maximized by the SNR increasing. Here, the EE is set to approximately 12.7 for $SNR \geq -10$ dB for 10 users, while the EE of the ISA in [11] is about 6.6. Hence, there are advantages such as energy consumption and savings for users, which increases the efficiency of the system networks. It is seen that the EE first increases with the increase in the number of users, signifying that the improvement in sensing performance exceeds the loss caused by less data transmission and more significant energy consumption. However, the rate of decrease in EE does not change significantly after a certain user through the transmission power increases. Therefore, an energy-efficient model can be designed by selecting a suitable number of users to avoid unnecessary power consumption growth. Hence, EE decreases as N further increases because the more cooperative users lead to more energy consumption, and the sensing performance cannot be improved anymore, thus resulting in the declining EE. Hence, it is necessary to balance energy consumption against the number of users when designing cooperative CR systems. Fig. 6 shows the comparison results among the maximum EE of this approach with that of the ISA algorithm under various $P(H_1)$ conditions. However, we set γ to -16 dB with varying $P(H_1)$s from 0 to 1. Similarly, our EE is much higher than the ISA for three different users. The EEs of all the compared schemes reduce with increasing $P(H_1)$, indicating the system performance of energy savings in the transmission phase. Similar to Figure 5, as the number of users in the network increases, the EE curve for each rule decreases, which indicates the correct network status. According to this form and standard of CR networks, there is at least a 60% increase in the gap between the user's group of two rules, which reduces the power consumption and save more energy in general.

In practice, a CR can enable the energy saving that can provide necessary information on radio environment and radio component characteristics and capabilities. It also determines the favorable configuration for the QoS requirement and accumulates knowledge on the interaction of radio component characteristics and environment, which is usually hard to model analytically. Similar to Fig. 3 and 4, Fig. 5 and Fig. 6 shows that our method with power allocation has better performance because power constraints can provide more flexibility for the transmission power allocation of SUs than the conventional ISA. Increasing the sensing time for each CR leads to increasing the number of samples, which improves the accuracy (smaller false alarm and missed detection probabilities) of sensing results. Smaller false alarm probability increases the chances of transmission and hence increases the throughput. From the SUs' perspective, a low false alarm means that more transmission opportunities can be used by the SUs, thus raising the throughput and the system EE. Additionally, smaller miss-detection probability reduces unuseful transmission cases in which the CR node interferes with the PU transmission. However, more sensing time provides a transmission time reduction, which decreases throughput.

VIII. CONCLUSION AND FUTURE WORK

In this work, we studied a CoMAC-based design to accelerate the cooperative sensing process by combining reporting and computation steps to optimize the EE using the fractional programming problem. According to the approximation of the local statistics suitable arithmetic mean function, we investigated the probabilities of detection and false alarm. We have also obtained the optimal sensing EE, which results in the minimum consumption of the average energy. Regarding the complex and non-convex nature of the joint optimization problem, we turned the problem into the same parameterized concave problem utilizing the fractional programming theory and the Dinkelbach method. We did this by presenting an energy-efficient iterative power allocation algorithm to solve the problem efficiently. The proposed EE method is superior over that of the ISA design, which provides a more desirable performance referring to simulation results obtained in this work. Beyond 5G networks, coverage performance increasing with the use of non-orthogonal multiple access (NOMA) and OFDMA technologies can be future study trends in this realm through considering the power-saving capabilities. Additionally, we have also stated the terms optimal spectrum allocation and maximum power allocation to reduce the minimum power consumption to save higher amounts of energy and maximize the total EE of the mentioned networks.

ACKNOWLEDGMENT

(Arash Ostovar and Yousaf Bin Zikria are co-first authors.)

APPENDIX A
PROOF OF THE LEMMA 1

For an arbitrary SU i, q_1 and q_2 denotes the optimal EE values corresponding to the transmission scheme (to the right side of **P2**). Assume that $q_1 > q_2$. Therefore,

$$\begin{aligned} F(q_2) &= \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_2\hat{E}(\tau_s, \lambda_s, L) \\ &> \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_2\hat{E}(\tau_s, \lambda_s, L) \\ &> \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_1\hat{E}(\tau_s, \lambda_s, L) \\ &= F(q_1). \end{aligned} \tag{42}$$

Hence, $F(q)$ is monotonically decreasing in q. On the other hand, let $(\tau_s, \lambda_s, L, \mathbf{p}')$ be an arbitrary feasible transmission approach, i.e.,

$$q' = \frac{\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}')}{\hat{E}(\tau_s, \lambda_s, L)}. \tag{43}$$

By definition,

$$\begin{aligned} F(q') &= \max_{\mathbf{p}} \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}') - q'\hat{E}(\tau_s, \lambda_s, L) \\ &\geq \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}') - q'\hat{E}(\tau_s, \lambda_s, L) = 0. \end{aligned} \tag{44}$$

This completes the proof.

APPENDIX B
PROOF OF THE THEOREM 2

First, we prove $q_{n+1} > q_n$ for all n with $F(q) > 0$ in such optimal values of q^*. By definition of q_{n+1}, we have $\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) = q_{n+1}\hat{E}(\tau_s, \lambda_s, L)$, thus $F(q_n) = \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_n\hat{E}(\tau_s, \lambda_s, L) = (q_{n+1} - q_n)\hat{E}(\tau_s, \lambda_s, L) > 0$. In addition, using $\hat{E}(\tau_s, \lambda_s, L) > 0$, we have $q_{n+1} > q_n$. Because $(\tau_s, \lambda_s, L, \mathbf{p}^*)$ gives the corresponding transmission rule, there exists

$$q^* = \frac{\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}^*)}{\hat{E}(\tau_s, \lambda_s, L)} \geq \frac{\hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p})}{\hat{E}(\tau_s, \lambda_s, L)}. \tag{45}$$

Thus, it is concluded that when

$$\begin{aligned} F(q^*) &= \max_{\mathbf{p}} \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q^*\hat{E}(\tau_s, \lambda_s, L) \\ &= \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}^*) - q^*\hat{E}(\tau_s, \lambda_s, L) \\ &= F(q^*; \tau_s, \lambda_s, L, \mathbf{p}^*) = 0. \end{aligned} \tag{46}$$

the optimal EE is accomplished by the optimal strategy. Then we proved $\lim_{n\to+\infty} q_n = q^*$. From [34], we have $F(q^*) = 0$, if $\lim_{n\to+\infty} q_n = q^\star \neq q^*$, we must have $q^\star < q^*$. By constructing a sequence $\lim_{n\to+\infty} F(q_n^\star) = F(q^\star) = 0$, hence, $\lim_{n\to+\infty} F(q_n) = F(q^*)$. Considering the continuous property of $F(.)$, we have $\lim_{n\to+\infty} q_n = q^*$. Therefore, the transmission strategy is optimal for the original program with objective function (25), i.e., it is the optimal EE strategy. This completes the proof.

APPENDIX C
PROOF OF THE LEMMA 2

Using the $\varepsilon - \delta$ definition of continuity, we can prove that $F(q) = 0$ is continuous in q. Further, $\lim_{p\to+\infty} F(q) = -\infty$ and $\lim_{p\to-\infty} F(q) = +\infty$. By the intermediate value theorem, $\exists q$, such that $F(q) = 0$.

APPENDIX D
PROOF OF THE LEMMA 3

Take $q_1 < q_2$, and let $\mathbf{p}^*$ maximize $K(\mathbf{p}) - qD(\mathbf{p})$. Then

$$\begin{aligned} F(q_2) &= \max\{K(\mathbf{p}) - q_2D(\mathbf{p})\} \\ &= K(\mathbf{p}^*) - q_2D(\mathbf{p}^*) < K(\mathbf{p}^*) - q_1D(\mathbf{p}^*) \\ &\leq \max\{K(\mathbf{p}) - q_1D(\mathbf{p})\} \\ &= F(q_1) \end{aligned} \tag{47}$$

We shall now prove the theorem. Note that it is sufficient to show that $F(\mathbf{p}, q)$ becomes smaller than ε with the number of iterations. Since $F(q) = \max\{F(\mathbf{p}, q)\}$, we only need to show that $F(q)$ becomes smaller than ε. We now show that q is non-increasing in successive iterations of the algorithm. If we use the subscript, n, to denote the values of variables on the nth iteration, we have:

$$\begin{aligned} 0 &= K(\mathbf{p}_{n-1}) - q_nD(\mathbf{p}_{n-1}) \\ &\leq \max\{K(\mathbf{p}_{n-1}) - q_nD(\mathbf{p}_{n-1})\} \\ &= F(q_n) \\ &= K(\mathbf{p}_n) - q_nD(\mathbf{p}_n) \\ &= q_{n+1}D(\mathbf{p}_n) - q_nD(\mathbf{p}_n) \\ &= (q_{n+1} - q_n)D(\mathbf{p}_n) \end{aligned} \tag{48}$$

Now, it follows that $q_{n+1} \geq q_n$, because $D(\mathbf{p}_n) > 0$. By Lemma 2, $F(q)$ is decreasing in q, and we just proved that q is non-increasing in successive iterations of the algorithm. Therefore, $F(q)$ is non-increasing in successive iterations of the algorithm. $F(q)$ does become zero, and it follows that $F(q)$ does become smaller than ε.

APPENDIX E
PROOF OF THE THEOREM 4

$F(q)$ is strictly monotonic decreasing, i.e., $F(q_1) < F(q_2)$ if $q_1 > q_2$. Let $\mathbf{p}$ maximize $F(q_1)$, then

$$\begin{aligned} F(q_1) &= \max_{\mathbf{p}} \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_1 \hat{E}(\tau_s, \lambda_s, L) \\ &= \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_1 \hat{E}(\tau_s, \lambda_s, L) \\ &< \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_2 \hat{E}(\tau_s, \lambda_s, L) \\ &\leq \max \hat{R}_s(\tau_s, \lambda_s, L, \mathbf{p}) - q_2 \hat{E}(\tau_s, \lambda_s, L) \\ &= F(q_2) \end{aligned} \tag{49}$$

REFERENCES

[1] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Phys. Commun.*, vol. 4, no. 1, pp. 40–62, Mar. 2011.
[2] B. Wang and K. J. Ray Liu, "Advances in cognitive radio networks: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, Feb. 2011.
[3] 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.
[4] J. Ma, G. Zhao, and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 11, pp. 4502–4507, Nov. 2008.
[5] G. Sharma and R. Sharma, "Joint sensing time and fusion rule threshold optimization for energy efficient CSS in cognitive radio sensor networks," *Int. J. Commun. Syst.*, vol. 31, no. 18, Sep. 2018, Art. no. e3820.
[6] N. S. A. G. Yari, M. L. Varus, and D. D. Van, "Energy-efficiency joint cooperative spectrum sensing and power allocation scheme for green cognitive radio network: A soft decision fusion approach," *Amer. J. Netw. Commun.*, vol. 7, no. 2, p. 6, 2018.
[7] X. Wu, J.-L. Xu, M. Chen, and J. Wang, "Optimal energy-efficient sensing and power allocation in cognitive radio networks," *Math. Problems Eng.*, vol. 2014, pp. 1–7, Aug. 2014.
[8] C. Wang, T. Song, J. Wu, Y. Yu, and J. Hu, "Energy-efficient cooperative spectrum sensing with reporting errors in hybrid spectrum sharing CRNs," *IEEE Access*, vol. 6, pp. 48391–48402, Sep. 2018.
[9] M. Robat Mili, L. Musavian, K. A. Hamdi, and F. Marvasti, "How to increase energy efficiency in cognitive radio networks," *IEEE Trans. Commun.*, vol. 64, no. 5, pp. 1829–1843, May 2016.
[10] G. Ozcan, M. C. Gursoy, N. Tran, and J. Tang, "Energy-efficient power allocation in cognitive radio systems with imperfect spectrum sensing," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3466–3481, Dec. 2016.
[11] M. Zheng, L. Chen, W. Liang, H. Yu, and J. Wu, "Energy-efficiency maximization for cooperative spectrum sensing in cognitive sensor networks," *IEEE Trans. Green Commun. Netw.*, vol. 1, no. 1, pp. 29–39, Mar. 2017.
[12] Z. Zhou, C. Zhang, J. Wang, B. Gu, S. Mumtaz, J. Rodriguez, and X. Zhao, "Energy-efficient resource allocation for energy harvesting-based cognitive Machine-to-Machine communications," *IEEE Trans. Cognit. Commun. Netw.*, vol. 5, no. 3, pp. 595–607, Sep. 2019.
[13] Z. Zhou, M. Dong, K. Ota, G. Wang, and L. T. Yang, "Energy-efficient resource allocation for D2D communications underlaying Cloud-RAN-Based LTE–A networks," *IEEE Internet Things J.*, vol. 3, no. 3, pp. 428–438, Jun. 2016.
[14] Z. Yang, W. Jiang, and G. Li, "Resource allocation for green cognitive radios: Energy efficiency maximization," *Wireless Commun. Mobile Comput.*, vol. 2018, pp. 1–16, Jul. 2018.
[15] A. Ostovar and Z. Chang, "Optimisation of cooperative spectrum sensing via optimal power allocation in cognitive radio networks," *IET Commun.*, vol. 11, no. 13, pp. 2116–2124, Oct. 2017.
[16] M. Ali and H. Nam, "Optimization of spectrum utilization in cooperative spectrum sensing," *Sensors*, vol. 19, no. 8, p. 1922, Apr. 2019.
[17] R. Fan, H. Jiang, Q. Guo, and Z. Zhang, "Joint optimal cooperative sensing and resource allocation in multichannel cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 60, no. 2, pp. 722–729, Feb. 2011.
[18] Z. Chen, X. Wang, and X. Zhang, "Continuous power allocation strategies for sensing-based multiband spectrum sharing," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2409–2419, Nov. 2013.
[19] B. Nazer and M. Gastpar, "Computation over multiple-access channels," *IEEE Trans. Inf. Theory*, vol. 53, no. 10, pp. 3498–3516, Oct. 2007.
[20] S. Verdú, *Multiuser Detection*. Cambridge, U.K.: Cambridge Univ. Press, 1998.
[21] M. Goldenbaum and S. Stańczak, "Robust analog function computation via wireless multiple-access channels," *IEEE Trans. Commun.*, vol. 61, no. 9, pp. 3863–3877, Sep. 2013.
[22] M. R. Spiegel, *Theory and Problems of Probability and Statistics*. New York, NY, USA: McGraw-Hill, 1992.
[23] S. Schwarz and M. Rupp, "Society in motion: Challenges for LTE and beyond mobile communications," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 76–83, May 2016.
[24] X. Zhang, M. Jia, L. Chen, J. Ma, and J. Qiu, "Filtered-OFDM–enabler for flexible waveform in the 5th generation cellular networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2014, pp. 1–6.
[25] S. Payami and F. Tufvesson, "Delay spread properties in a measured massive MIMO system at 2.6 GHz," in *Proc. IEEE 24th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Sep. 2013, pp. 53–57.
[26] F. Meshkati, H. V. Poor, and S. C. Schwartz, "Energy-efficient resource allocation in wireless networks," *IEEE Signal Process. Mag.*, vol. 24, no. 3, pp. 58–68, May 2007.
[27] 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.
[28] X. Huang, T. Han, and N. Ansari, "On green-energy-powered cognitive radio networks," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 827–842, 2nd Quart., 2015.
[29] X. Zhang, Q. Zhang, S. Zhang, and Y. Ji, "Energy efficiency optimization of cognitive radio networks with continuous spectrum sensing," in *Proc. 8th Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Yangzhou, China, Oct. 2016, pp. 1–5.
[30] Z. Shi, K. Hung Li, T. Tan, and K. C. Teh, "Energy efficient cognitive radio network based on multiband sensing and spectrum sharing," *IET Commun.*, vol. 8, no. 9, pp. 1499–1507, Jun. 2014.
[31] 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.
[32] A. R. Kulkarni and A. Agarwal, "Energy-efficient QoS based route management in cognitive radio networks," in *Proc. IEEE Int. Conf. Data Sci. Data Intensive Syst.*, Sydney, NSW, Australia, Dec. 2015, pp. 304–310.
[33] M. Awasthi, M. J. Nigam, and V. Kumar, "Optimal sensing and transmission of energy efficient cognitive radio networks," *Wireless Pers. Commun.*, vol. 111, no. 2, pp. 1283–1294, Mar. 2020.
[34] W. Dinkelbach, "On nonlinear fractional programming," *Manage. Sci.*, vol. 13, no. 7, pp. 492–498, Mar. 1967.
[35] Y. Xu and X. Zhao, "Robust adaptive power control for cognitive radio networks," *IET Signal Process.*, vol. 10, no. 1, pp. 19–27, Sep. 2016.
[36] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.
[37] S. Schaible and T. Ibaraki, "Fractional programming," *Eur. J. Oper. Res.*, vol. 12, no. 4, pp. 325–338, Apr. 1983.
[38] R. Zhang, "On peak versus average interference power constraints for protecting primary users in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 4, pp. 2112–2120, Apr. 2009.
[39] S. Maleki, A. Pandharipande, and G. Leus, "Energy-efficient distributed spectrum sensing for cognitive sensor networks," *IEEE Sensors J.*, vol. 11, no. 3, pp. 565–573, Mar. 2011.
[40] S. Boyd, L. Xiao, and A. Mutapcic, "Subgradient methods," Stanford Univ., Stanford, CA, USA, Lect. Notes EE392o, 2003, pp. 2003–2004.

ARASH OSTOVAR was born in Shiraz, Iran, in August 1991. He received the B.Eng. degree in information and communications technology (ICT) engineering from the Shiraz Pasargad Higher Education Institute, Shiraz, in 2013, and the M.Sc. degree in telecommunication system engineering from the Shiraz University of Technology, Shiraz, in 2015. His current research interests include cognitive radio networks, next-generation wireless communications, the Internet of Things, optical wireless communications, and green communications. Since 2016, he has been serving as a Reviewer of some prestigious international journals.

YOUSAF BIN ZIKRIA (Senior Member, IEEE) received the Ph.D. degree from the Department of Information and Communication Engineering, Yeungnam University, Gyeongsan, South Korea, in 2016. He is currently working as an Assistant Professor with the Department of Information and Communication Engineering, College of Engineering, Yeungnam University. He has more than ten years of experience in research, academia, and industry in the field of information and communication engineering and computer science. He has authored more than 60 scientific peer-reviewed journals, conferences, patents, and book chapters.

HYUNG SEOK KIM (Member, IEEE) received the B.S. degree from the School of Electrical Engineering, Seoul National University, South Korea, and the M.S. and Ph.D. degrees from the School of Electrical Engineering and Computer Engineering, Seoul National University. In 2003 and 2004, he held a Visiting Researcher position with the University of Virginia. From 2004 to 2006, he was with the Telecommunication Research and Development Center, Samsung Electronics. He is currently a Faculty Member with the Department of Information and Communication Engineering, Sejong University. His research interest includes networking with special emphasis on wireless communication and visual light communication.

RASHID ALI (Member, IEEE) received the B.S. degree in information technology from Gomal University, Pakistan, in 2007, the master's degree in computer science (advanced network design) from University West, Sweden, in 2010, and the Ph.D. degree in diploma in information and communication engineering from the Department of Information and Communication Engineering, Yeungnam University, South Korea, in 2019. He is currently an Assistant Professor with the School of Intelligent Mechatronics Engineering, Sejong University, Seoul, South Korea. His research interests include next-generation wireless local area networks (IEEE 802.11ax/ah), unlicensed wireless networks in 5G, reinforcement learning, and federated reinforcement learning techniques for wireless networks.