Cooperative Spectrum Sensing for Beyond-5G Networks in Fading Environments

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ABSTRACT

The advent of pervasive wireless systems faces several challenges due to the massive data traffic growth resulting from the interconnection of billions of new devices. This makes it essential to provide smart decision-making in identifying available spectrum resources by sensing the radio frequency environment. In this study, we aim to improve the spectrum sensing process and enhance the detection efficiency of secondary users (sensing devices) in identifying primary users (transmitting devices). We consider a scenario in which secondary users are affected by noise and fading, and employ distributed detection and data fusion to combine data from geographically distributed sensors. The results show that collaborative spectrum sensing, where multiple SUs share their sensing data, significantly enhances detection performance. By applying optimization techniques to assign optimal weight vectors to the sensors, we further increase the detection performance of the primary user, where each one is affected by different noise factors. The study reveals that detection performance improves as more users collaborate, and this improvement is validated through scenarios with varying SNR values.

CCS CONCEPTS

• **Networks**;

KEYWORDS

Beyond-5G, 5G networks, Spectrum Sensing, Collaborative Sensing.

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1 INTRODUCTION

As wireless communications continue to grow with the advent of 5G technologies, new intelligent systems will be necessary to help organization, managing, and interact with the surrounding Radio Frequency (RF) environment. This trend is becoming even more demanding as new wireless services are rising, such as virtual/augmented reality, autonomous driving, smart industry and agriculture, Internet of Things, etc. This growth may pose potential risks in communication networks, leading to severe interference [1]. A possible solution to go beyond this issue is to employ cognitive radio (CR) systems, where a device can learn and adapt to its RF environment. The reason is that current fixed spectrum assignment policies often result in inefficient spectrum utilization. Cognitive radio technology enables access to unused frequency bands, known as spectrum holes, to improve spectrum allocation efficiency, a process called spectrum sensing [2]. Spectrum sensing has two aims: (i) efficiently identifying and exploiting spectrum holes; (ii) SU trying to avoid harmful interference to primary users (PU) by switching to available bands or exploiting spectrum holes. Consequently, detection performance in spectrum sensing is crucial for the performance of both primary and SUs in cognitive radio networks.

A crucial aspect of CRs involves selecting appropriate sensing techniques for each scenario. Energy detection [3] is a widely used non-coherent detection technique in spectrum sensing, because it does not require prior knowledge of primary user signals and offers implementation simplicity. However, energy detection has some drawbacks. For example, it often requires considerable time to achieve the desired detection accuracy, and the performance is impacted by variations in noise power. A significant limitation is its inability to distinguish PU signals from SU signals, or spread spectrum signals with low signal-to-noise ratio (SNR) [4]. Finally, the performance of energy detection algorithms heavily relies on environmental conditions [2, 4, 5], where noise sources and imperfections like multipath fading, shadowing, and receiver uncertainty issues may substantially impact the detection performance of spectrum sensing [6].

Considering these practical challenges, it becomes crucial to develop strategies that enhance the efficiency and reliability of spectrum sensing techniques, and ensure optimal performance in cognitive radio networks. One approach to overcome this limitation is by utilizing cooperative sensing technology in CR networks. In this scenario, SUs can cooperate and share the sensing results with other SUs, compensating the limitations of individual observations made by each user. As a result, the overall detection performance can be significantly enhanced. This is the reason why cooperative spectrum sensing is considered a powerful and efficient strategy to tackle issues like multipath fading and shadowing, and to reduce the uncertainty of the measurements. Several elements can affect the cooperation gain including cooperation strategy, sensing techniques, control channel and reporting, data fusion, hypothesis testing, user selection and knowledge base [4].

In this paper, we propose a simple cooperation model where SUs collaboratively detect the presence of PUs through a parallel fusion network, i.e. we neglect the presence of data traffic to focus on the detection performance. The local SU measurements are forwarded to a Fusion Center (FC), which combines the reported data through data fusion and can therefore make global decisions using binary hypothesis testing. The rest of the paper is organized as follows: sec. 2 provides some background information on cooperative sensing and discusses related works; sec. 3 analyzes the problem of cooperative spectrum sensing and in sec. 4 we focus on the methodology used; sec. 5 presents the results obtained; finally, sec. 6 concludes the paper and discusses possible future works.

2 BACKGROUND AND RELATED WORK

Cooperative spectrum sensing has proven to be an effective approach in mitigating issues in traditional spectrum sensing techniques, particularly fading and shadowing effects [7]. Nonetheless, the focus of spectrum sensing may vary depending on the specific technologies employed and the radio frequency environment, highlighting the need for adaptability and customization in sensing techniques. Typically, cooperative sensing involves three main processes: local sensing, reporting, and data fusion. In local sensing, a SU monitors the immediate spectral environment to detect the presence or absence of PUs. Reporting is the process where the SUs share their local sensing results with other SUs or a FC. Finally, data fusion involves merging sensing data from multiple SUs to form a comprehensive detection result.

Based on how the SUs communicate and share their sensing information, we can divide the cooperation strategies into three categories, where each of these methods introduces different overhead and achieves various levels of cooperative gain. (i) *Centralized* cooperative spectrum sensing is based on a central node, often referred as FC, which controls the process of cooperative sensing [6, 8, 9]. It collects all the local sensing information from the participating SUs to determine the presence of PUs. The centralized approach improves the precision of detection by joining the combined sensing abilities of numerous SUs. Nonetheless, it brings about considerable overhead as it requires all SUs to relay information to the FC, which can result in bottlenecks and delays. (ii) *Distributed* cooperative spectrum sensing, in which SUs collaborates directly with each other, without relying on a FC [10]. Each SU shares its sensing data with other SUs, combines its own data with the received information, and repeatedly sends the combined results to other SUs until a certain local criterion is met. This method enhances scalability and robustness but requires sophisticated protocols and algorithms. Despite these advantages, it can still introduce higher overhead than centralized cooperative spectrum sensing. (iii) *Relay-assisted* lies between centralized and distributed cooperative sensing [11, 12]. In scenarios where some SUs have poor reporting channels and cannot share their sensing information, the overall cooperative gain drops. In such cases, the relay-assisted method can improve the cooperative gain. For example, SUs with poor reporting channels can use nearby SUs with strong reporting channels as relays to assist in forwarding the sensing results.

In order to combine local sensing information and detect unoccupied frequencies in the spectrum, two primary methods have been introduced: soft combining and hard combining. The soft combining method involves cooperating SUs sending their entire local sensing samples to the FC. This approach offers higher accuracy but is more complex. Conversely, in the hard combining method, the cooperating SUs make local decisions and transmit only the decision bits to the FC. Although this method is less complex, it tends to have lower accuracy compared to the soft combining approach. Cooperative strategies often use linear combinations of estimates gathered from several SUs to provide the sensing result. There are numerous optimization approaches that can be implemented in these strategies, such as maximal ratio combining [13], Neyman-Pearson criterion [13], adaptive exponential-weighting windows [14], or methods based on minimizing the mean-squared error [15].

In the specific context of spectrum sensing in fading environments, a study investigated the optimization of cooperative spectrum sensing over Rayleigh fading channels with perfect feedback channels [16]. This work was later extended to incorporate Lee's imperfect feedback channels and hard decision combining [17], as well as optimization over various non-composite and composite fading channels [18]. Reference [19] presents a comparative study of different decision fusion rules in the context of wide-band spectrum sensing, taking into account various channel errors. This study focuses on the evaluation of miss-detection and overall error probability. In another work, [20], the optimization of cooperative spectrum sensing based on energy detection is investigated, considering noise and generalized fading channels. On the other hand, [21] proposes a fusion decision approach that employs a weighted strategy. In this method, the FC breaks down spectrum sensing into time intervals to improve the accuracy of cooperative decisions. More recently, the k-means clustering algorithm [22], has been employed to evaluate cooperative spectrum sensing performance in generalized fading channels. Moreover, machine learning techniques and the application of neural networks for decision-making in cooperative spectrum sensing aims to develop an adaptable model capable of delivering optimal classification accuracy in changing radio environments [23]. Finally, in [24], authors propose a federated learning-based spectrum sensing (FLSS) algorithm to improve the efficiency of training and testing the neural

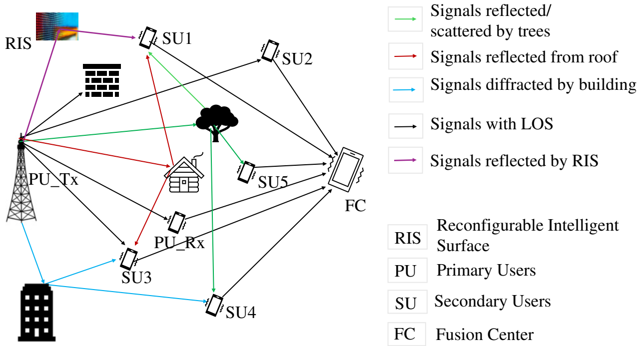

Figure 1: The cooperative sensing model of parallel fusion.

network model and to reduce communication overhead between the FC and SUs. Independently of the technique used, in this paper we quantify the performance of cooperative spectrum sensing in fading environments and study the gain of collaboration.

3 COOPERATIVE SENSING SCENARIO

The objective of the present study is to optimize the sensing procedure at the central FC and enhance the detection efficiency when SUs attempt to detect a single PU. As shown in Fig. 1, we consider a given topology where the SUs are affected by different noise and fading factors, or where signal are reflected by Reconfigurable Intelligent Surfaces (RIS). In the end, all SUs will transmit all their sensing information to a central location. Here, the FC will make decisions aimed at optimizing the detection performance, taking into account the varying situations and Signal-to-Noise Ratios (SNRs) that each SU encounters.

There are different methodologies that can be used to represent the cooperation of CR devices in spectrum sensing, with the main emphasis being on how SUs collaborate to obtain the best possible performance. As illustrated in Fig. 1, the distributed detection and data fusion (or parallel fusion model) is the most often used method. Parallel fusion models determine how data are combined and decisions are made in an effort to improve detection performance in distributed signal processing techniques. A central processor receives observations of SUs from a number of geographically dispersed sensors. In the figure, the solid lines indicate signals originated from PU_Tx, or reflected from the physical environment, and then local observations from the SUs are reported to the FC displayed with a black line again. The FC uses the data fusion to merge the sensing measurements and performs binary hypothesis testing to reach a global decision. Thus, the SUs report their sensing results and the FC takes the decision on the channel or frequency band of interest. Once this local sensing data has been combined, the FC broadcasts its cooperative conclusion to all collaborating SUs. In general, from Fig. 1 the entire process of cooperative sensing is clear, i.e. local sensing, data reporting and data fusion [4]. Note that, in the present paper, we neglect communication overhead and latency introduced by the cooperative sensing process, which will be analyzed and optimized in future work.

4 PROPOSED METHODOLOGY

The cooperative sensing process begins with individual spectrum sensing performed by each SU, referred to as local sensing. Let m denote the number of collaborating SUs. In general, local sensing for primary signal detection can be represented as a binary hypothesis problem, which can be expressed as follows:

$$x_m(n) = \begin{cases} v(n), & \text{if } H_0 \text{ holds} \\ h_m s(n) + v(n), & \text{if } H_1 \text{ holds} \end{cases}. \tag{1}$$

Here, $x_m(n)$ represents the signal received at the m-th SU. The transmitted PU signal is denoted by $s(n)$. Also, $v(n)$ refers to the zero-mean additive white Gaussian noise (AWGN), given as $\mathcal{N}\left(0, \sigma_m^2\right)$. The hypotheses H_0 and H_1 correspond to the absence and presence, respectively, of the PU signal in the frequency band of interest. Additionally, the signal is affected by a channel gain/attenuation h_m which directly depends on the fading and shadowing in the CR network environment. To incorporate these effects, the PU signal is modelled as $h_m(n) = \sqrt{\beta\left(\frac{d_0}{d_m}\right)^{\alpha} 10^{-\frac{\psi_m}{10}}}$. In this model, β represents a constant related to antenna characteristics and average attenuation, α is the path-loss exponent, d_m denotes the distance between the m-th secondary user (SU-m) and the PU , d_0 is the reference distance, and ψ_m is a Gaussian-distributed random variable with zero mean and variance σ_m^2 to account for the shadow fading of the channel between the PU and SU-m [25].

In a collaborative scheme [26], the test statistic consists of a set of energy statistics denoted by $y = \{T_1(x), T_2(x), \ldots, T_m(x)\}$, which comprises energy estimates from all m participating nodes. The energy statistics can be represented as

$$T_m(x) = \sum_{n=0}^{N} |x(n)|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_m \tag{2}$$

where γ_m denotes the test threshold for distinguishing between the hypotheses.

The central limit theorem [3] suggests that the summation of statistics can be approximated to a normal distribution when N is large enough (typically, $N \geq 20$ is adequate in practical scenarios). Then, under the two hypotheses, we obtain $y \sim \mathcal{N}(\mu_0, \Sigma_0)$ under H_0 and $\mathcal{N} \sim (\mu_1, \Sigma_1)$ under H_1. The mean values for hypotheses H_0 and H_1 are given by $\mu_0 = N\left[\sigma_1^2, \sigma_2^2, \ldots, \sigma_m^2\right]^T$ and $\mu_1 = \left[(N+\eta_1)\,\sigma_1^2, (N+\eta_2)\,\sigma_2^2, \ldots, (N+\eta_m)\,\sigma_m^2\right]^T$, respectively. Here, η_m is the Signal-to-Noise Ratio (SNR) at the m-th SU node, given as

$$\eta_m = \frac{|h_m|^2}{\sigma_m^2} \sum_{n=0}^{N-1} |s_n|^2. \tag{3}$$

Also, the variances of the statistics are given by $\Sigma_0 = 2N \cdot \operatorname{diag}[\sigma_1^4, \sigma_2^4, \ldots, \sigma_m^4]^T$, and $\Sigma_1 = \operatorname{diag}[2\sigma_1^4\,(N+2\eta_1), 2\sigma_2^4(N+2\eta_2), \ldots, 2\sigma_m^4\,(N+2\eta_m)]^T$ under hypotheses H_0 and H_1, respectively. It is worth recalling that the diag[] operator creates the diagonal of a square matrix with the elements of a given vector, while $[]^T$ represents the transpose operation for vectors or matrices.

In order to mitigate the errors introduced by multipath fading and shadowing, and to extend beyond the scope of a single sensor, we can adopt an optimized operative scheme [27]. A detector structure is then employed in this scheme, which can be expressed as $L = \omega^T y$, where L is the global decision statistic, ω is a weight vector that needs to be determined, and y is the vector of local energy detected by individual nodes. The weight vector ω represents the contribution of each SU to the global decision. For instance, if a node produces a high SNR observation, which is more likely to lead to a correct decision, it should be assigned a larger weight in the weight vector ω.

In order to assess the detection performance, we define the probabilities of detection and false alarm as $P_d = P(H_1|H_1)$ and $P_f = P(H_0|H_1)$, respectively. For a large number of samples, the linear combination of multiple Gaussian random variables remains Gaussian, allowing us to approximate the probability of false alarm and the probability of detection as follows:

$$\begin{aligned} P_f = P(H_0|H_1) =& Q\left(\frac{\gamma - \mu_0^T \omega}{\sqrt{\omega \Sigma_0 \omega^T}}\right), \\ P_d = P(H_1|H_1) =& Q\left(\frac{\gamma - \mu_1^T \omega}{\sqrt{\omega \Sigma_1 \omega^T}}\right) \end{aligned} \tag{4}$$

where $Q(x) = \frac{1}{2\pi}\int_x^{\infty} e^{-\frac{\tau^2}{2}} d\tau$ is the Q-function. As an important note, we make the assumption that each node can estimate the noise variance, denoted as σ_m^2, and share it along with its energy estimations, $T_m(x)$, with its neighbors in the CR network. This allows each node to experience different SNRs, depending on the varying conditions each node encounters.

We can formulate an optimization problem to maximize the probability of detecting the spectral hole, thereby increasing the opportunistic spectrum utilization of the targeted frequency band. This optimization is subject to a constraint on the false alarm probability, ensuring that the sensing process remains within acceptable limits. The problem can be formulated as:

$$\begin{aligned} &\max_{\omega} \; P_d \\ &\text{s.t. } P_f \leq \epsilon \end{aligned} \tag{5}$$

where ϵ represents the maximum threshold on false alarms.

5 RESULTS

Before exploring the cooperative multi-sensor scenario, let's consider a simpler case involving a single SU and a single PU. This will help to lay the foundation for understanding more complex situations, involving multiple sensors and users. Notably, the ultimate detection performance of any spectrum sensor is directly impacted by the SNR, commonly referred to as the SNR wall. As indicated in Eq. 3, this SNR factor is closely related to the fading environment and signal power. To illustrate this relationship, we plot the miss-detection probability, i.e., $1 - P_d$, in terms of predetermined false alarm probability, in Fig. 2 (a) for two SNR values, 3 and 10 dB. Form the figure, it is evident that the optimum detection performance, characterized by a minimum miss-detection probability, can be attained by adjusting the false probability value. Indeed, this optimal performance directly depends on the SNR values, as demonstrated in Fig. 2 (b). Here, for a given false probability, we observe that the detection probability increases as the SNR increases.

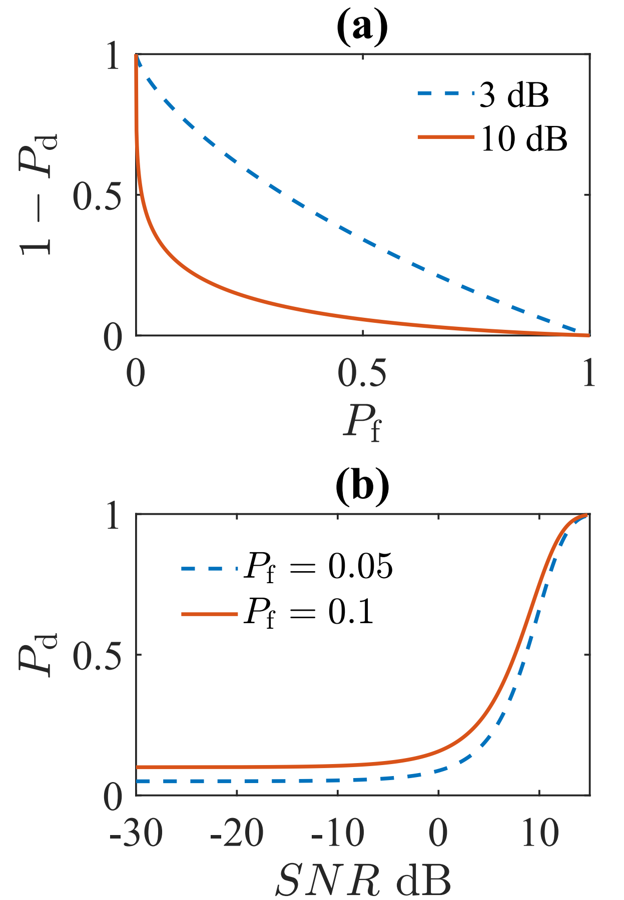

Figure 2: Spectrum sensing detection under noise uncertainty for a single SU. (a) Missed detection probability, i.e., $(1 - P_d)$, as a function of false alarm probability for two SNR values: 3 and 10 dB. (b) Detection probability, i.e., (P_d), as a function of SNR for given false alarm probabilities: $(P_f = 0.05)$ and $(P_f = 0.1)$.

To improve spectrum sensing performance, we now enable multiple SUs to collaborate by sharing their decision statistics with a central FC. For simplicity, we initially assume that all m SUs experience independent and identically distributed fading/shadowing with the same average SNR. In this scenario, the enhancement in detection performance, in terms of detection and false-alarm probabilities for the collaborative scheme, can be expressed as $1 - (1 - P_d)^m$ and $1 - (1 - P_f)^m$, respectively. It becomes evident that the collaborative scheme increases both the detection probability and false-alarm probability compared to local sensing. However, the overall outcome is an improvement in detection performance, as depicted in Fig. 3 (a). As Fig. 3 (a) shows, as m increases, the collaborative scheme is capable of outperforming local sensing $m = 1$. This is because, with a larger m, the high probabilities are aggregated. The results indicate a significant improvement in the required average SNR for detection.

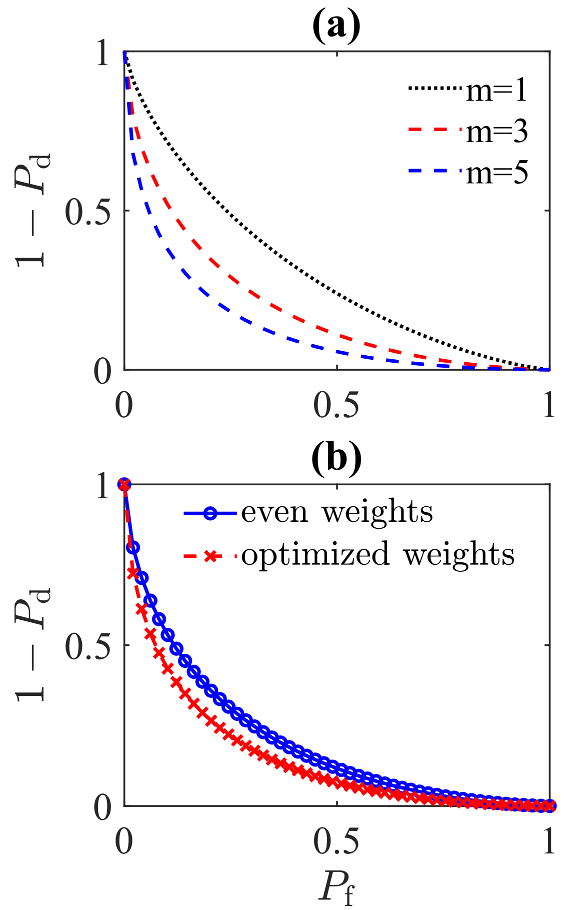

Figure 3: Cooperative spectrum sensing detection under noise uncertainty. (a) Missed detection probability, i.e., ($1-P_d$), as a function of false alarm probability for one ($m = 1$), three ($m = 3$), and five ($m = 5$) SUs with identical SNR value of 3 dB. (b) Missed detection probability, i.e., ($1 - P_d$), as a function of false alarm probability with five sensors ($m = 5$), in two cases: even weights and optimized weights in a non-uniform SNR scenario with -20.00, -1.20, 1.77, 3.52, and 4.77 dB, for the five SUs respectively.

In a more realistic scenario, all sensors may experience different environmental conditions and can be affected by varying fading and shadowing factors. For example, as depicted in Fig. 3 (b), SU1, SU2, SU3, SU4, and SU5 are subject to multipath and shadow fading. This will potentially decrease their efficiency in detecting the PUs. Additionally, SU5 is assumed to be not in range of the primary receiver (PU_Rx). This may result in interference between SU5's transmissions and reception at PU_Rx. However, due to spatial diversity, it is unlikely that all spatially distributed SUs will face fading or receiver issues simultaneously. If a certain SU, such as SU2 in Fig. 1, detects a strong PU signal and collaborates by sharing its sensing results, the proposed cooperative scheme enhances the overall detection performance. This is why we employ the optimization protocol described in Eq. 5, to assign an optimal vector weight (ω) and improve performance. Indeed, the extent of this improvement also depends on the specific optimization techniques utilized.

Fig. 3 (b) shows a scenario with five SUs and one PU, each having different SNR values: -20, -1.20, 1.77, 3.52, and 4.77 dB. Initially, we assign equal weights to the SUs and plot the missed detection probability versus the false alarm probability. Note that equal weights are optimal when all users have the same SNR. However, nodes experience different SNR, optimizing the weight vector can significantly enhance performance compared to using equal weights. Indeed, we tested this algorithm for other combinations of SNRs, and the optimization always resulted in better performance in cases of non-uniform SNRs.

6 CONCLUSIONS

Due to the exponential growth in wireless communications, the implementation of intelligent decision-making processes to identify available spectrum is needed. The present study proposes a cooperative spectrum sensing scheme to improve the detection efficiency, particularly in scenarios where SUs are impacted by noise and fading factors. Exploiting data fusion techniques to aggregate data from geographically dispersed sensors, our findings demonstrate that collaborative spectrum sensing markedly increases detection probability. Moreover, we propose optimization techniques to assign optimal weight vectors to the SUs, improving the performance of the proposed scheme. Indeed, our study highlights the importance of optimizing weight vectors in non-uniform SNR environments, which significantly boosts detection accuracy.

Future research could explore the integration of machine learning algorithms to further refine the spectrum sensing process and adapt to dynamic network environments. Also, federated learning could be exploited to reduce communication overhead between the FC and SUs, still maintaining good performance. Overall, the present work demonstrates that collaborative and optimized spectrum sensing is a powerful tool to address the challenges posed by 5G networks and paves the way for more efficient and reliable wireless communication systems.

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