# Optimization for Prediction-Driven Cooperative Spectrum Sensing in Cognitive Radio Networks

Dawei Nie, Wenjuan Yu, Qiang Ni, and Haris Pervaiz
School of Computing and Communications, InfoLab21, Lancaster University, UK
Emails: {d.nie, w.yu8, q.ni, h.b.pervaiz}@lancaster.ac.uk

***Abstract*—Empirical studies have observed that the spectrum usage in practice follows regular patterns. Machine learning (ML)-based spectrum prediction techniques can thus be used jointly with cooperative sensing in cognitive radio networks (CRNs). In this paper, we propose a novel cluster-based sensing-after-prediction scheme and aim to reduce the total energy consumption of a CRN. An integer programming problem is formulated that minimizes the cluster size and optimizes the decision threshold, while guaranteeing the system accuracy requirement. To solve this challenging optimization problem, the relaxation technique is used which transforms the optimization problem into a tractable problem. The solution to the relaxed problem serves as a foundation for the solution to the original integer programming. Finally, a low-complexity search algorithm is proposed which achieves the global optimum, as it obtains the same performance with exhaustive search. Simulation results demonstrate that the total energy consumption of CRN is greatly reduced by applying our clustered sensing-after-prediction scheme.**

***Index Terms*—Spectrum sensing, cognitive radio, energy consumption, spectrum prediction, decision threshold.**

## I. Introduction

To alleviate the severe spectrum scarcity issue in wireless communications, different technologies have been proposed such as cognitive radio (CR), millimeter-wave (mmWave) communications, and non-orthogonal multiple access [1], [2]. Particular attention has been drawn to cognitive radio networks (CRNs) since they can greatly improve the spectrum utilization by allowing secondary users (SUs) to share the licensed spectrum with primary users (PUs) [3]–[5]. Cognitive radios sense the surrounding radio frequency (RF) environment and make decisions as an intelligent wireless communication system [6]–[10]. More specifically, to improve the sensing accuracy, cooperative sensing (CS) can be utilized that requires multiple SUs to sense together and fuses all the sensing results at a fusion center (FC). Studies have shown that the sensing performance can be greatly improved with an increase in the number of cooperative partners [11]. However, this will result in an increased energy consumption in CRNs.

Energy consumption is another key issue of CRNs because SUs are normally battery-powered mobile devices. When they conduct CS, a large amount of energy can be consumed. As a result, energy efficiency and energy consumption during spectrum sensing become two important topics in energy-constrained CRNs. To effectively reduce energy consumption while maintaining system reliability, a joint and proactive approach that fully exploits sensing and prediction techniques is now considered to be a promising method [12], [13]. Empirical studies have shown that in real-life spectrum usage, certain patterns exist [14]. This enables us to use machine learning (ML)-based prediction methods for CRNs, leading to a reduced total energy consumption without sacrificing the system accuracy. It has been shown that the accuracy of spectrum prediction is normally close to and sometimes even exceeds the accuracy of spectrum sensing, depending on the randomness of system environment, the complexity and cost of ML algorithms [8], [15].

Many studies have focused on the joint prediction-sensing scheme for CRNs and analyzed the performance from different perspectives. A joint prediction-sensing model was introduced in [12] that utilizes a parallel fusion-based cooperative spectrum prediction scheme to minimize errors and increase efficiency for energy-constrained CRNs. The accuracy was discussed in [12] using simulation results, while the exact analytical expressions were not given. A spectrum sharing model based on spectrum prediction and sensing was proposed in [13]. The authors investigated a joint optimization design of transmit beamforming at the secondary base station (BS) with energy and sensing time constraints, while the probability models in [13] were from the perspective of correlation between single-user and cooperative results. The above-mentioned papers mainly adopt the joint prediction-sensing scheme to enhance users' performance. They did not minimize the number of users participating in CS or study the tradeoff between system performance and cluster size. We believe that while an acceptable accuracy performance is guaranteed, the system scale and the total energy consumption can be greatly reduced by finding the minimum number of required users and allowing the system has other users performing different functions.

In this paper, we propose a novel cluster-based sensing-after-prediction scheme. It adopts an adjustable decision threshold, which decides when the scheme shall not accept the prediction result and opt for sensing instead. We aim to reduce the total energy consumption of a CRN by minimizing the cluster size and finding the optimal decision threshold for a given accuracy requirement. The overall contributions of this paper are summarized as follows:

- We first derive the analytical expressions for system accuracy and energy consumption for the proposed sensing-after-prediction scheme, where the accuracy is validated through Monte Carlo simulations.
- An integer programming problem that minimizes the cluster size for a given system accuracy requirement is formulated. To solve it effectively, we first analyze a relaxed problem that maximizes the system accuracy for a given cluster size. The optimal decision threshold is derived analytically.
- A low-complexity search algorithm is finally proposed to solve the original integer programming. The minimum cluster size and its optimal decision threshold are obtained. Numerical results indicate that the required number of users and energy consumption are greatly reduced without violating the accuracy requirement.

## II. System Model

Consider a classic CRN that consists of one PU, $N$ SUs, and one FC. The system model is shown in Fig. 1. Let us consider the primary channel has a regular usage pattern and the accuracy of ML prediction is known. A proportion of SUs are combined into a cluster to predict PU channel states. This cluster is defined as a learning cluster and consists of $n$ SUs, where each SU in the cluster performs spectrum prediction and reports their results to FC. At the FC, the cooperative decision can be provided based on the adaptive decision threshold and the collected prediction results from SUs in the learning cluster. Based on the cooperative prediction (CP) decision at the FC, the system will opt for CS for a more assured result or decide to take an action straightaway. PU and SUs are assumed to be synchronized by a time-slotted system. In each slot, SUs access the channel in time division multiple access (TDMA). Each time slot (T) is divided into three parts, named as prediction stage, reaction stage and transmission stage respectively. The slot structure of the proposed system for each SU is shown in Table I. The detailed explanations of sub-slots in Table I are given below.

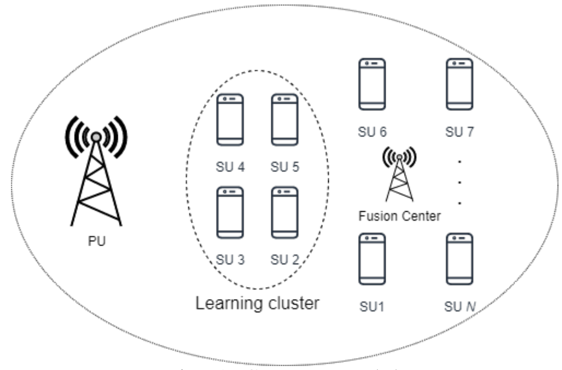



Fig. 1: System model.

TABLE I: Time and energy structure of one time slot.

| Prediction Stage | Reaction Stage | Action Stage |
|---|---|---|
| $e_{\mathrm{M}}$ | DM: 0 | 0 if channel busy |
| | IM: $e_{\mathrm{S}}$ | $e_{\mathrm{T}}$ if channel idle |
| $\longleftarrow \mathrm{t_P} \longrightarrow$ | $\longleftarrow \mathrm{t_R} \longrightarrow$ | $\longleftarrow \mathrm{t_T} \longrightarrow$ |

- $t_{\mathrm{P}}$: Prediction stage. Each SU in the cluster performs spectrum prediction using ML techniques and reports the prediction result to FC. The system will obtain the CP decision at the FC and turn to determinate (DM) or indeterminate (IM) state at the end of this stage. If the system considers that the prediction result is accurate, this stage will end with a DM state. Otherwise it ends with an IM state [12]. Slot-wise energy spent during prediction stage for each SU is represented by $e_{\mathrm{M}}$.
- $t_{\mathrm{R}}$: Reaction stage. All SUs do not perform spectrum sensing and remain silent if the system state is DM. On the other hand, if the system state is IM, spectrum sensing is performed at each SU and the CS decision is obtained at FC based on the sensing results. $e_{\mathrm{S}}$ represents the energy spent during spectrum sensing for each SU.
- $t_{\mathrm{T}}$: Transmission stage. Transmission is decided based on the CP or CS decision obtained in the first two stages. If the system believes that the PU channel state is idle, the transmission will start with an energy consumption $e_{\mathrm{T}}$.

In the prediction stage, after each SU in the learning cluster performs spectrum prediction, a binary decision $D_i$ is forwarded to the FC. $D_i$ being 0 represents that the SU predicts that PU channel is idle, while $D_i$ equal to 1 means that the SU $i$ predicts that the PU channel is busy. Prediction results of SUs in the cluster are fused together according to the logic rule in (1) after all the 1-bit decisions, i.e., $D_i$, $1 \leq i \leq n$, are received at FC.

$$Y = \sum_{i=1}^{n} D_i \begin{cases} \geq \sigma, & \text{DM} \\ \leq n-\sigma, & \text{DM} \\ \text{otherwise.} & \text{IM} \end{cases} \tag{1}$$

$\sigma$ in (1) is defined as the decision threshold to distinguish DM and IM states. This threshold indicates that if at least $\sigma$ SUs' prediction results are the same, the system will enter the DM state and take the CP result, which is what the majority of SUs (at least $\sigma$ SUs) agree on, as the final decision. Here, it is required that $\sigma \geq \lceil \frac{n+1}{2} \rceil$ because it is natural to make sure at least half of the users make the same prediction when entering DM state. If the required decision accuracy is high, a larger threshold $\sigma$ should be set. If the system is in DM state, then all SUs will stay silent and the transmission action is made based on the CP decision. Otherwise, all $n$ SUs start sensing and the transmission action is made according to the CS result.

After performing independent spectrum sensing, each SU reports its binary decision to the FC. There are two key metrics to evaluate the performance of spectrum sensing, namely the probability of detection ($P_d$) and the probability of false alarm ($P_f$) respectively. $P_d$ indicates the probability that the SU declares the primary channel is occupied when the primary channel is indeed busy. $P_f$ indicates the probability that the SU declares the primary channel is occupied when the primary channel is idle. At the FC, all binary decisions are fused together according to a fusion rule. A "$q$-out-of-$m$" voting rule is used for CS decision in our system [16]. For example, the primary channel is sensed to be busy if at least $q$ sensing results of $m$ SUs declare the channel as occupied. Therefore, the detection probability and the false alarm probability of CS decision are respectively given by

$$Q_d = \sum_{l=q}^{m} \binom{m}{l} P_d^l \left(1 - P_d\right)^{m-l}, \tag{2}$$

$$Q_f = \sum_{l=q}^{m} \binom{m}{l} P_f^l \left(1 - P_f\right)^{m-l}. \tag{3}$$

## III. Problem Formulation and Optimization

In order to reduce the total energy consumption, we formulate an optimization problem to minimize the learning cluster size, while maintaining a required system accuracy.

### A. Problem Formulation

In this section, $p$ is assumed to be the probability of ML prediction being right for a single SU. The prediction depends on the usage history of primary channel. The probability that at least $q$ prediction results of $n$ SUs are correct is given by

$$P_{\text{acc}} = \sum_{l=q}^{n} \binom{n}{l} p^l (1-p)^{n-l}. \tag{4}$$

Recall that the threshold $\sigma$ indicates that if at least $\sigma$ prediction results are the same, the system will be in DM

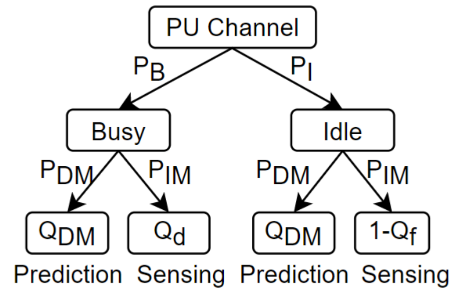



Fig. 2: Decision tree diagram of the system.

state and accept the CP result. Because the CP result can be either correct or wrong, the probability of entering DM state can be calculated as the probability that at least $\sigma$ predictions are right and at least $\sigma$ predictions are wrong. Hence, the probability of entering DM state, i.e., $P_{\text{DM}}$, can be expressed in (5a). Assume that in DM state, the probability of CP result being right is denoted by $P_a$. Then, the accuracy of CP, i.e., $Q_{\text{DM}}$, is equal to $\frac{P_a}{P_{\text{DM}}}$, yielding (5b). The probability of the system in IM state is then given by $P_{\text{IM}} = 1 - P_{\text{DM}}$.

The decision tree diagram of the system is shown in Fig. 2. The parameters on the branches, i.e., $P_{\text{B}}$, $P_{\text{I}}$, $P_{\text{DM}}$, and $P_{\text{IM}}$, indicate the probabilities of states, while $Q_{\text{DM}}$, $Q_{\text{d}}$ and $1-Q_{\text{f}}$ each represent corresponding state's accuracy. $P_{\text{B}}$ and $P_{\text{I}}$ are the probabilities of PU in busy and idle respectively, where $P_{\text{B}} + P_{\text{I}} = 1$. Let $Q_{\text{S}}$ denote the accuracy of CS, expressed as $Q_{\text{S}} = P_{\text{B}}Q_d + P_{\text{I}}(1-Q_f)$. According to Fig. 2, the system accuracy can be finally obtained and expressed in (5c). Monte-Carlo simulations will be provided to verify the accuracy of (5c) in Section IV.

In order to obtain the total energy consumption, we assume that there are $L$ slots in total during one experiment period. The expression of the total energy consumption for each SU, in Joule, is given by

$$E = Le_{\text{M}} + LP_{\text{IM}}e_{\text{S}}, \tag{6}$$

where $Le_{\text{M}}$ and $LP_{\text{IM}}e_{\text{S}}$ are consumed energy during spectrum prediction and sensing, respectively. We define that $E_{\text{S}} = LP_{\text{IM}}e_{\text{S}}$. In comparison, for the traditional CS scheme, the total energy consumption is $E_{S_1} = Le_{\text{S}}$.

Recall that our aim is to reduce energy consumption by minimizing the cluster size. Given a minimum accuracy requirement $\epsilon$, the minimum learning cluster size $n$ and the optimal decision threshold $\sigma$ need to be obtained. It is assumed that the devices used for spectrum sensing are equal to cluster size $n$, and the majority rule ($q = \lceil \frac{n+1}{2} \rceil$) is used for CS. The system accuracy can be expresses as a function of cluster size $n$ and threshold $\sigma$, i.e., $Q(\sigma, n)$ in (5d). The optimization problem P1 can

$$P_{\mathrm{DM}} = \sum_{l=\sigma}^{n} \left[ \binom{n}{l} p^l (1-p)^{n-l} + \binom{n}{l} p^{n-l} (1-p)^l \right], \tag{5a}$$

$$Q_{\mathrm{DM}} = \frac{\sum_{l=\sigma}^{n} \binom{n}{l} p^l (1-p)^{n-l}}{\sum_{l=\sigma}^{n} \left[ \binom{n}{l} p^l (1-p)^{n-l} + \binom{n}{l} p^{n-l} (1-p)^l \right]}, \tag{5b}$$

$$Q(n,\sigma) = P_{\mathrm{DM}} Q_{\mathrm{DM}} + P_{\mathrm{IM}} \left( P_{\mathrm{B}} Q_d + P_{\mathrm{I}} \left(1 - Q_f\right)\right) = P_{\mathrm{DM}} Q_{\mathrm{DM}} + P_{\mathrm{IM}} Q_{\mathrm{S}} \tag{5c}$$

$$= \sum_{l=\sigma}^{n} \binom{n}{l} p^l (1-p)^{n-l} + Q_{\mathrm{S}} \left(1 - \sum_{l=\sigma}^{n} \binom{n}{l} p^l (1-p)^{n-l} - \sum_{l=\sigma}^{n} \binom{n}{l} p^{n-l} (1-p)^l \right). \tag{5d}$$

be formulated as

$$\text{P1:} \quad \min_{\sigma} \quad n \tag{7a}$$

$$\text{s.t. } Q(\sigma, n) \geq \epsilon, \tag{7b}$$

$$\left\lceil \frac{n+1}{2} \right\rceil \leq \sigma \leq n, \tag{7c}$$

$$1 \leq n \leq N, \tag{7d}$$

$$n, N, \sigma \in \mathbb{Z}. \tag{7e}$$

### *B. Accuracy Analysis*

The formulated optimization problem P1 is an integer programming which is challenging to solve. In order to solve it, let us first focus on the system accuracy $Q(\sigma)$ by considering that the cluster size $n$ is a fixed value in (5d). Then, we relax the integer variable $\sigma$ by treating it as a continuous variable. The optimal threshold $\sigma^*$ that maximizes the system accuracy for a certain $n$ can be obtained by taking the first derivative of $Q(\sigma)$ with respect to $\sigma$. Inspired by [3], we get that $\frac{\partial Q(\sigma)}{\partial \sigma} \approx Q(\sigma+1) - Q(\sigma)$, which yields

$$\frac{\partial Q(\sigma)}{\partial \sigma} = (Q_{\mathrm{S}} - 1) \binom{n}{\sigma} p^{\sigma} (1-p)^{n-\sigma} + Q_{\mathrm{S}} \binom{n}{\sigma} p^{n-\sigma} (1-p)^{\sigma}. \tag{8}$$

The optimal threshold $\sigma^*$ is obtained when $\frac{\partial Q(\sigma)}{\partial \sigma} = 0$. Hence, the expression of $\sigma^*$ can be given in (9).

$$\sigma^* = \begin{cases} \left\lceil \frac{1}{2} \log_{\frac{p}{1-p}} \frac{Q_{\mathrm{S}}}{1-Q_{\mathrm{S}}} \left( \frac{p}{1-p} \right)^n \right\rceil & \text{when } n > 1, \\ 1 & \text{when } n = 1. \end{cases} \tag{9}$$

Note that $\sigma^*$ should be in the range of $n \geq \sigma^* \geq \left\lceil \frac{n+1}{2} \right\rceil$ in order to make (9) feasible. To satisfy the feasible condition, we substitute (9) into the range of $\sigma^*$ which results in a relationship between $p$ and $Q_{\mathrm{S}}$, given below.

$$\begin{cases} \alpha > Q_{\mathrm{S}} > 0.5 & \text{when } n \text{ is even and } p > 0.5, \\ \alpha < Q_{\mathrm{S}} < 0.5 & \text{when } n \text{ is even and } p < 0.5, \\ \alpha > Q_{\mathrm{S}} > 1-p & \text{when } n \text{ is odd and } p > 0.5, \\ \alpha < Q_{\mathrm{S}} < 1-p & \text{when } n \text{ is odd and } p < 0.5. \end{cases} \tag{10}$$

where $\alpha = \frac{p^n}{(1-p)^n + p^n}$ and $Q_s \neq p \neq 0.5$. This indicates that $\sigma^*$ that maximizes the system accuracy for a fixed $n$ is given in (9), while the condition (10) is satisfied. If the parameters do not meet the limitations provided in (10), the accuracy expression will become a monotonic function and the maximum accuracy is obtained when $\sigma_m = n$ or $\sigma_m = \left\lceil \frac{n+1}{2} \right\rceil$. Here, $\sigma_m$ is the threshold that maximizes the system accuracy for a fixed $n$ when (10) is not satisfied.

### *C. Search Algorithm*

The optimal threshold that maximizes the system accuracy for a fixed cluster size $n$ is now obtained. A search algorithm can be then developed to solve the original integer programming problem P1. Firstly, for $n = 1 : N$, we first calculate the $\sigma^*$ by using (9) for each cluster size $n$ if the parameters meet the limitations provided in (10). The first pair of $(n, \sigma^*)$ that meets the accuracy requirement $Q(n, \sigma) \geq \epsilon$ can be found. The minimum cluster size required and its optimal threshold are therefore given by $(n, \sigma^*)$. On the other hand, if the parameters do not meet the limitations provided in (10), the optimal threshold is $\sigma_m$ and $\sigma_m = n$ or $\sigma_m = \left\lceil \frac{n+1}{2} \right\rceil$. The minimum cluster size required and its optimal threshold are therefore given by $(n, \sigma_m)$. If none of such pair is found, we continue to search by using $n = n+1$ until $n = N$. The Pseudo code of the proposed search algorithm is given in Algorithm 1. Since the loop from 1 to $N$ stops when the algorithm finds the optimal size $n$, the complexity is therefore $O(n^2)$. If exhaustive search is used instead, the complexity will be $O(N^3)$. The complexity of our proposed algorithm is much lower than the exhaustive search.

## IV. Simulation Results

In this section, we simulate the cluster-based sensing-after-prediction scheme in a cooperative manner to validate the derived analytical expressions and the performance of the proposed search algorithm. More specifically, we compare the outputs of exhaustive search and the proposed search algorithm given in Section III-C under the constraints of system accuracy. We assume that $e_{\mathrm{S}} = 100$ mJ, $e_{\mathrm{M}} = 10$ mJ, $p = 0.8$, $L = 1000$, $P_f = 0.1$

**Algorithm 1** Proposed Search Algorithm

**Input:** $N$, $\epsilon$, $P_d$, $P_f$, $p$, $P_{\text{B}}$, $P_{\text{I}}$.

```
Set initial value n = 1. Calculate Q_S.
while n ≤ N do
    if p and Q_S do not satisfy (10) then
        Q*(n, σ_m) = max[Q(n, n), Q(n, ⌈(n+1)/2⌉)];
        if Q* ≥ ε then
            (n_opt, σ_opt) = (n, σ_m);
            return
        end if
    else if p and Q_S meet the limitations in (10) then
        Calculate σ* by using (9), Q* = Q(n, σ*);
        if Q* ≥ ε then
            (n_opt, σ_opt) = (n, σ*);
            return
        end if
    end if
    n = n + 1;
end while
```

**Output:** $(n_{\text{opt}}, \sigma_{\text{opt}})$

and $P_d = 0.775$ [16], unless otherwise indicated. For Monte-Carlo simulations, the ML prediction accuracy is 0.85, i.e., $p = 0.85$, in order to clearly compare the data under small fluctuation. Finally, we have that $P_{\text{B}} = 1/6$ and $P_{\text{I}} = 5/6$, inspired by [14] and [12]. It is also assumed that the accuracy requirement $\epsilon = 0.995$ and the total number of SUs in the network is 50, i.e., $N = 50$.

Fig. 3 is plotted to validate the accuracy of the derived analytical expression of system accuracy given in (5d). It can be noted that the analytical results closely match with Monte-Carlo simulations. Some differences in the results are mainly due to the random numbers and small cluster sizes in the prediction decision states. Fig. 4 shows the system accuracy versus the threshold $\sigma$ for different cluster sizes $n$. From this figure, it can be observed that there exists an optimal threshold for each given cluster size $n$ where the system reaches its maximum accuracy.

Fig. 5(a) and Fig. 5(b) illustrate the energy consumption versus the cluster size $n$, for the proposed scheme and benchmark schemes. The optimal threshold is used for both figures. Fig. 5(a) shows that the average energy consumption ($E_{\text{S}}$) of SUs for the sensing-after-prediction scheme becomes much smaller than the traditional CS scheme [3] at large cluster sizes. Recall that $E_{\text{S}} = LP_{\text{IM}}e_{\text{S}}$. When the cluster size becomes larger, the probability of entering the IM state, i.e., $P_{\text{IM}}$, is reduced. Hence, there is a smaller probability that SUs will perform sensing, resulting in a smaller energy consumption. Fig. 5(b) shows that the total energy consumption for the sensing-after-prediction scheme also becomes smaller at large cluster sizes. The total energy consumption greatly

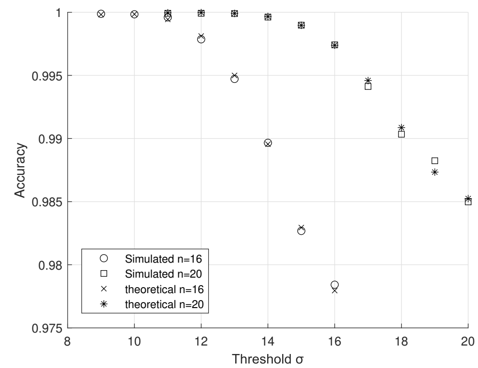



Fig. 3: System accuracy vs. threshold $\sigma$ for the comparison of analytical expressions and Monte Carlo results where $p = 0.85$.

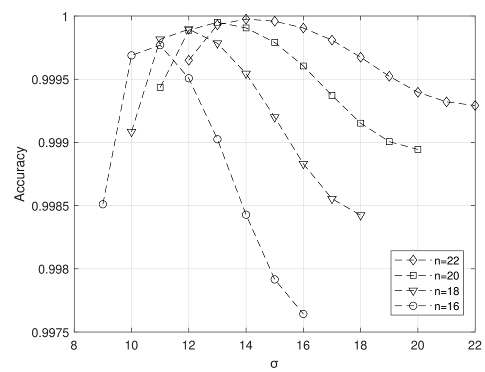
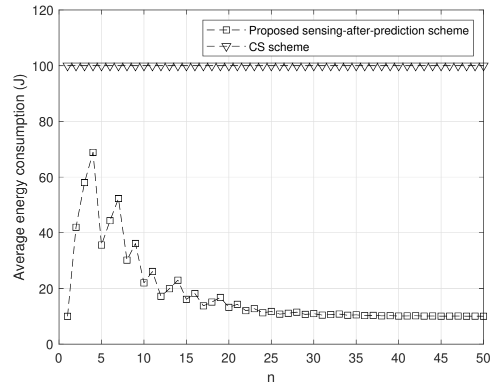


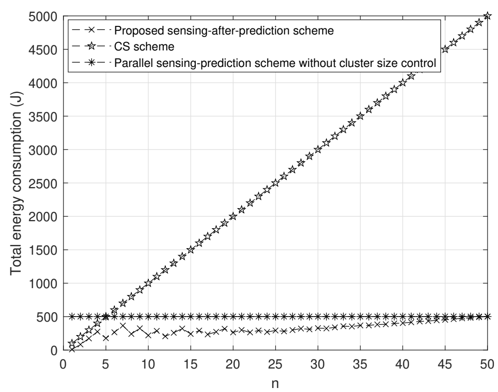

Fig. 4: System accuracy vs. threshold $\sigma$ for different values of cluster size $n$ where $p = 0.8$.

increases with cluster size for the CS system. On the contrary, the proposed scheme has smaller energy consumption and the consumed energy slowly increases with cluster size since the energy consumption of spectrum prediction is considered to be smaller than spectrum sensing. Fig. 5(b) also plots a parallel sensing-prediction scheme as a benchmark [12]. The parallel scheme is assumed to have a fixed cluster size $N$ and its $P_{\text{DM}}$ value is same as our proposed scheme. Fig. 5(b) shows that our proposed scheme has better energy performance than the parallel sensing-prediction scheme.

To compare the performance of the proposed search algorithm and exhaustive search, Table II is provided. From a practical point of view, the prediction accuracy $p$ is set to be larger than 0.6. Table II shows that the obtained optimal solutions of the proposed search algorithm perfectly match with exhaustive search results for different ML prediction accuracy values, which means the proposed search algorithm finds the global optimum.




(a) The comparison of average energy consumption between the cluster-based sensing-after-prediction scheme and the traditional CS scheme




(b) The comparison of total energy consumption between the cluster-based sensing-after-prediction scheme, the traditional CS scheme and the parallel sensing-prediction scheme

Fig. 5: Energy consumption vs. cluster size $n$.

TABLE II: $(n_{\text{opt}}, \sigma_{\text{opt}})$ of the proposed algorithm and exhaustive search.

| ML accuracy $p$ | 0.6 | 0.7 | 0.8 | 0.9 | 1 |
|---|---|---|---|---|---|
| Our algorithm | (11,11) | (11,9) | (7,6) | (5,4) | (1,1) |
| Exhaustive Search | (11,11) | (11,9) | (7,6) | (5,4) | (1,1) |

## V. Conclusions

We proposed a cluster-based sensing-after-prediction CS scheme to reduce the total energy consumption. After obtaining analytical expressions for the system accuracy and energy consumption, an optimization problem that minimizes cluster size for a given accuracy requirement has been formulated. To solve it effectively, we derived an analytical solution for the optimal decision threshold that maximizes accuracy after problem relaxation. Then, the original integer programming problem is solved by a low-complexity search algorithm. Simulations show that the energy consumption is largely reduced and the outputs of the proposed search algorithm perfectly match with exhaustive search results.

## References


[1] S. Chen, B. Ren, Q. Gao, S. Kang, S. Sun, and K. Niu, "Pattern division multiple access—a novel nonorthogonal multiple access for fifth-generation radio networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 4, pp. 3185–3196, Apr. 2017.

[2] P. Yang, L. Kong, and G. Chen, "Spectrum sharing for 5g/6g urllc: Research frontiers and standards," *IEEE Communications Standards Magazine*, vol. 5, no. 2, pp. 120–125, 2021.

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

[4] W. Yu, A. U. Quddus, S. Vahid, and R. Tafazolli, "Opportunistic spectrum access in support of ultra-reliable and low latency communications," in *2018 IEEE Globecom Workshops (GC Wkshps)*, 2018, pp. 1–7.

[5] Q. Ni and C. Zarakovitis, "Nash bargaining game theoretic scheduling for joint channel and power allocation in cognitive radio systems," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 1, pp. 70–81, Jan 2012.

[6] Y. Pei, Y. C. Liang, K. C. Teh, and K. H. Li, "Sensing-throughput tradeoff for cognitive radio networks: A multiple-channel scenario," *IEEE Int. Symp. Pers. Indoor Mob. Radio Commun. PIMRC*, vol. 7, no. 4, p. 1326–1337, 2009.

[7] Y.-C. Liang, K.-C. Chen, G.-Y. Li, and P. Mahonen, "Cognitive radio networking and communications: an overview," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 7, pp. 3386 – 3407, Sept. 2011.

[8] T. Cody and P. A. Beling, "Heterogeneous transfer in deep learning for spectrogram classification in cognitive communications," in *2021 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAAW)*, 2021, pp. 1–5.

[9] S. Aghabeiki, C. Hallet, N. E.-R. Noutehou, N. Rassem, I. Adjali, and M. Ben Mabrouk, "Machine-learning-based spectrum sensing enhancement for software-defined radio applications," in *2021 IEEE Cognitive Communications for Aerospace Applications Workshop (CCAAW)*, 2021, pp. 1–6.

[10] P. Nimudomsuk, M. Sanguanwattanaraks, K. Srisomboon, and W. Lee, "A performance comparison of spectrum sensing exploiting machine learning algorithms," in *2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, 2021, pp. 102–105.

[11] G. Ganesan and Y. G. Li, "Cooperative spectrum sensing in cognitive radio networks," *Proc. IEEE Symp. New Frontiers Dynamic Spectrum Access Networks (DySPAN'05)*, pp. 137–143, Nov 2005.

[12] P. Chauhan, S. K. Deka, B. C. Chatterjee, and N. Sarma, "Cooperative spectrum prediction-driven sensing for energy constrained cognitive radio networks," *IEEE Access*, vol. 9, pp. 26 107 – 26 118, Feb. 2021.

[13] V.-D. Nguyen and O.-S. Shin, "Cooperative prediction-and-sensing-based spectrum sharing in cognitive radio networks," *IEEE Transactions on Cognitive Communications and Networking*, vol. 4, no. 1, Mar. 2018.

[14] M. Wellens, J. Riihijärvi, and P. Mähönen, "Empirical time and frequency domain models of spectrum use," *Physical Communication*, vol. 2, no. 1, pp. 10–32, 2009, cognitive Radio Networks: Algorithms and System Design.

[15] M. K. Giri and S. Majumder, "Extreme learning machine based cooperative spectrum sensing in cognitive radio networks," in *2020 7th International Conference on Signal Processing and Integrated Networks (SPIN)*, 2020, pp. 636–641.

[16] H. Wang, L. Lightfoot, and T. Li, "On pry-layer security of cognitive radio: Collaborative sensing under malicious attacks," *2010 44th Annual Conference on Information Sciences and Systems (CISS)*, Mar. 2010.