Optimal Distributed Data Collection for Asynchronous Cognitive Radio Networks

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***Abstract*—As a promising communication paradigm, Cognitive Radio Networks (CRNs) have paved a road for Secondary Users (SUs) to opportunistically exploit unused licensed spectrum without causing unacceptable interference to Primary Users (PUs). In this paper, we study the distributed data collection problem for asynchronous CRNs, which has not been addressed before. First, we study the Proper Carrier-sensing Range (PCR) for SUs. By working with this PCR, an SU can successfully conduct data transmission without disturbing the activities of PUs and other SUs. Subsequently, based on the PCR, we propose an Asynchronous Distributed Data Collection (ADDC) algorithm with fairness consideration for CRNs. ADDC collects data of a snapshot to the base station in a distributed manner without any time synchronization requirement. The algorithm is scalable and more practical compared with centralized and synchronized algorithms. Through comprehensive theoretical analysis, we show that ADDC is order-optimal in terms of delay and capacity, as long as an SU has a positive probability to access the spectrum. Finally, extensive simulation results indicate that ADDC can effectively finish a data collection task and significantly reduce data collection delay.**

***Keywords*-cognitive radio networks; data collection; distributed algorithm; asynchronous wireless network; delay; capacity;**

I. INTRODUCTION

Wireless spectrum is one of the most precious resources for wireless networks. With the fast growth of wireless networks, communications over the free (unlicensed) spectrum have become more and more crowded. On the contrary, according to the report from the Federal Communications Commission (FCC) [1], the utilization of the spectrum assigned to licensed users varies from 15% to 85% temporally and geographically, which is very inefficient. This necessitates a new communication paradigm, named Cognitive Radio Networks (CRNs), enabling a user equipped with a cognitive radio to sense and learn the communication environment, and further exploit the instantaneous assigned (licensed) spectrum opportunistically without causing unacceptable interference to the licensed users [2].

Under the CRN communication paradigm, a *secondary network*, which consists of Secondary Users (SUs) (unlicensed users) equipped with cognitive radios, is coexisted with a *primary network*, which consists of Primary Users (PUs) (licensed users). The SUs sense and exploit spectrum opportunistically and share the same space, time, and spectrum with PUs. For an SU, when it has some data for transmission, it begins to sense the communication environment. If there is a spectrum opportunity, *i.e.* the data transmission of the SU will not cause unacceptable interference to any PU, meanwhile, the receiver of this data transmission is out of the interference range of any primary transmitter, then the SU can initiate a data transmission. During the data transmission of an SU, if a PU comes back to transmit/receive data, the SU has to immediately handoff the spectrum being occupied to guarantee that its data transmission does not interfere with the communications of PUs.

Numerous efforts have been spent for different issues in CRNs, including spectrum sensing [3]-[5], spectrum access, scheduling, and management [6]-[8], capacity/throughput/delay scaling laws [9]-[11], network connectivity [15], [16], routing protocols [17]-[19], multicast communication [20], [21], and *etc*. Data collection is a common and important operation in wireless networks, as well as in CRNs, which can be used to gather data from an entire network. However, not too much effort has been devoted on data collection for CRNs, especially practical distributed data collection in asynchronous CRNs.

Intuitively, CRNs are distributed asynchronous systems and thus prefer distributed algorithms. First, CRNs tend to be large-scale distributed wireless systems, for which it is difficult and expensive (sometimes, even impossible) to obtain real-time network running information for network management and configuration. Second, the deploy environment of CRNs may be ever-changing, which may induce significant degradation of centralized and synchronized algorithms. Third, in CRNs, some existing SUs might leave the network and some new SUs might join the network at any time. In this case, centralized and synchronized algorithms cannot adapt to these network changes in real time. Finally and most importantly, SUs should not cause any unacceptable interference to PUs, which makes the status of a CRN change more frequently and unpredictably. Hence, centralized and synchronized algorithms are not preferable for CRNs. Therefore, we investigate the distributed data collection issue in asynchronous CRNs in this paper.

Without overall network information and time synchronization, it is very complicated to study distributed data collection algorithms in asynchronous CRNs. There are four main challenges. First, data transmissions of SUs should not cause any unacceptable interference to PUs. Therefore, how to guarantee that a secondary network does not interrupt the primary network in a distributed manner is a challenge. Second, centralized algorithms can make an overall optimized decision, however, it is difficult for distributed algorithms to guarantee an overall optimized solution by using only local network information. Hence, how to design an effective distributed data collection algorithm for CRNs is another challenge. Third, in an asynchronous CRN, many data collisions, interference, and retransmissions occur due to lack of time synchronization, followed by capacity degradation and unfairness among data flows. Therefore, how to overcome the problems induced by lack of time synchronization and meanwhile taking fairness into consideration is also a challenge. Finally, how to theoretically analyze the performance of the proposed data collection algorithm and obtain the corresponding delay bound is another challenge issue.

To address the aforementioned challenges, we propose a distributed data collection algorithm for CRNs without time synchronization requirement. First, we study the *Proper Carrier-sensing Range* (PCR) for an SU. Working with the PCR and the Re-Start (RS) mode[1], an SU can successfully conduct data transmission as long as there are no active PUs or SUs within its PCR, and will not cause unacceptable interference to any activities of PUs. Considering these restrictions, we propose a Connected Dominating Set (CDS)-based data collection algorithm, named *Asynchronous Distributed Data Collection* (ADDC), for CRNs. Through theoretical analysis, we show that ADDC is order-optimal as long as an SU has a positive probability to access the spectrum. We also conduct extensive simulations to validate the performance of ADDC. Simulation results show that ADDC can effectively gather all the data packets to the base station and significantly reduce data collection delay.

The rest of the paper is organized as follows. In Section II, we summarize the related work. In Section III, we describe the proposed network model and interference model. The derived PCR and ADDC are presented in Section IV, followed by theoretical analysis of the delay and capacity performance of ADDC. We examine ADDC via simulations in Section V, and finally conclude this paper in Section VI.

II. Related Work

Ever since the CRN communication paradigm was proposed, extensive research has been conducted on spectrum sensing [3]-[5], spectrum access, scheduling and management [6]-[8], capacity/throughput/delay scaling laws [9]-[11], network connectivity [15], [16], routing protocols [17]-[19], and multicast communication [20], [21].

Spectrum Sensing: Since the spectrum is one of the most precious resources in CRNs, to sense and learn the instantaneous spectrum opportunities in the communication environment is crucial in designing an efficient CRN. In [3]-[5], the authors studied the spectrum sensing problem. In [3], the authors investigated the problem of optimal Cooperative Sensing Scheduling (CSS) and parameter design to achieve energy efficiency in CRNs using the framework of Partially Observable Markov Decision Process (POMDP). In [4], the authors studied the throughput-efficient sequential channel sensing and probing problem. An optimal use-or-skip decision strategy that maximizes a CRN's average throughput is derived by formulating the sequential sensing and probing process as a rate-of-return problem, which can be solved by optimal stopping theory. In [5], the authors proposed an efficient periodic in-band sensing algorithm that optimizes sensing-frequency and sensing-time by minimizing sensing overhead while meeting the detect ability requirements. In the proposed algorithm, the noise uncertainty and inter-CRN interference which affect detection performance are also considered.

Spectrum Access, Scheduling, and Management: An elegant spectrum access/scheduling/management scheme can improve spectrum utilization efficiency and reduce the interference to PUs caused by SUs. This issue attracts much attention [6]-[8]. In [6], the authors investigated the performance limitation on the throughput of CRNs under the PU packet collision constraint. They proposed an optimum spectrum access strategy under generic PU traffic patterns with prefect sensing, and a modified threshold-based spectrum access strategy which achieves close-to-optimal performance without perfect sensing. In [7], practical unicast and convergecast scheduling schemes for SUs are introduced. In [8], the authors formulated price competition in a CRN as a game, taking into account both bandwidth uncertainty and spatial reuse. They analyzed the game in a single slot as well as its repeated case. For each case, the authors proved the existence of a Nash equilibrium and provided a method to explicitly compute it.

Capacity/Throughput/Delay Scaling Laws: The capacity, throughput, and delay scaling issues for CRNs are studied in [9]-[11] and references therein. By introducing preservation regions around primary receivers and avoidance regions around primary base stations, the authors proposed two modified multi-hop routing protocols for SUs in [9]. Based on percolation theory, they showed that when the secondary network is denser than the primary network and the primary network throughput is subject to a fractional loss, both networks can simultaneously achieve the same throughput scaling law as a stand-alone network. The authors in [10] studied the capacity and delay-throughput scaling laws for CRNs. Under certain assumptions, they showed that

[1]With the RS mode, a receiver will switch to receive the stronger signal as long as the Signal-to-Interference Ratio (SIR) threshold for the stronger signal can be satisfied [22].

both primary and secondary networks can achieve the same capacity and delay-throughput scaling laws. The authors in [11] established an Information propagation Speed (IPS) model in CRNs, and obtained the maximum network IPS that maximizes IPS across a network topology over an infinite plane.

Connectivity: Following the work of [14], which studies the connectivity of ad hoc networks via percolation theory, the authors in [15], [16] and references therein studied the connectivity issue of CRNs. They exploited theories and techniques from continuum percolation and ergodicity to derive the scaling law of the minimum multihop delay with respect to the source-destination distance in CRNs.

Routing Protocols: In [17]-[19], the authors considered the routing protocols for CRNs. To better characterize the unique features of CRNs, the authors in [17] proposed some new routing metrics, which include accumulated spectrum temperature, highest spectrum temperature, and mixed spectrum temperature to account for the time-varying spectrum availability. In [18], the authors investigated the problem of finding the Least-Priced Path (LPP) between a source and a destination in CRNs. They obtained an optimal route selection and payment determination mechanism that minimizes the price tag of the selected route and at the same time guarantees truthful cost reports from SUs. By modelling the vacancy of licensed bands with a series of random variables, introducing corresponding scheduling constraints and flow routing constraints, the authors in [19] studied the joint routing and link scheduling problem of multihop CRNs.

Multicast Communication: Multicast is an important operation in wired/wireless networks, as well as in CRNs [20]. The authors in [20] proposed an optimization framework for multicast operations for CRNs. In the proposed framework, a multicast is accomplished by carefully tuning the power. Concurrently, SUs opportunistically perform cooperative transmissions using locally idle primary channels in order to mitigate multicast loss and delay effects. In another work [21], the authors studied the video multicast issue in CRNs. With the objectives of optimizing the overall received video quality and achieving proportional fairness among multicast users, they model the CRN video multicast as an optimization problem considering important design factors such as scalable video coding, video rate control, spectrum sensing, dynamic spectrum access, modulation, scheduling, retransmission, and PU protection.

Remarks: Very few of the above mentioned works consider the data collection issue in CRNs, especially distributed data collection in asynchronous CRNs. Furthermore, most of the existing works for CRNs either are centralized algorithms or require time synchronization. However, as pointed out in Section I, CRNs tend to be distributed systems and prefer distributed and asynchronous algorithms. Motivated by this fact, we propose a distributed data collection algorithm for CRNs without time synchronization requirement. Through theoretical analysis, we show that the proposed algorithm successfully achieves order-optimal data collection capacity as centralized data collection algorithms for traditional wireless networks.

III. System Model

In this paper, we consider a secondary network consisting of n SUs coexisted with a primary network consisting of N PUs deployed in an area with size $A = c_0 n$. Both networks share the same time, space, and spectrum.

Primary Network: The primary network consists of N *independent and identically distributed* (*i.i.d.*) PUs (*licensed users*), denoted by $S_1, S_2, \cdots, S_N$. Define $V_p = \{S_1, S_2, \cdots, S_N\}$. To guarantee the secondary network has some spectrum opportunity, we assume the primary network satisfies the *locally finite* property, *i.e.* $N/A < \infty$. This is reasonable since otherwise the secondary network may never have an opportunity to access the spectrum. The maximum transmission radius of PUs is R and all the PUs have a fixed power P_p.

The network time is slotted and the duration of a time slot is τ. We use a generalized probabilistic model to describe the data transmission activities of PUs. During a particular time slot, each PU transmits data (performing as a transmitter) with probability p_t. Generally speaking, given a specific probabilistic distribution, such as the Poisson distribution and the Uniform distribution, of the activities of the primary network, p_t can be determined accordingly.

Secondary Network: The secondary network consists of $n > N$ single-radio SUs denoted by $s_1, s_2, \cdots, s_n$ and one single-radio *base station* (sink) denoted by s_b. All the SUs and the base station are also *i.i.d.*. The maximum transmission radius of SUs is r. Therefore, the secondary network can be modeled as a graph $G_s = (V_s, E_s)$, where $V_s = \{s_b, s_1, s_2, \cdots, s_n\}$, and E_s is the link set consisting of all the possible links formed by SUs in V_s. We assume G_s is connected. All the SUs have the same working power denoted by P_s. Note that, for $\forall s_i, s_j \in V_s$, even if there is a link between s_i and s_j as shown in Fig. 1, it does not imply that s_i can successfully transmit data to s_j. Besides the possible wireless interference from other SUs as in traditional wireless networks, two more reasons may cause the failure: (i) the data transmission from s_i may interfere with some receiving activity of a PU, *e.g.* S_1 in Fig. 1; (ii) the data receiving activity at s_j may be interfered by some transmission activity of PUs, *e.g.* S_2 in Fig. 1. Therefore, to carry out a data transmission between an SU pair, having spectrum opportunity is necessary.

We formally define a *data collection task* as follows. At a particular time slot t, every SU in the secondary network produces a data packet of size B. The set of all the n data packets produced by SUs at time t is called a *snapshot*. The task of gathering all the n data packets of a snapshot to the base station without any data aggregation is called

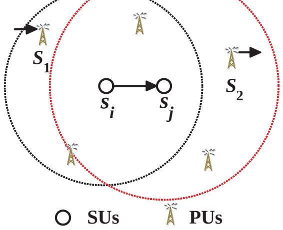


Figure 1. Illustration of the communication between s_i and s_j.

a *data collection task*. The *data collection delay* is the time consumption to finish a data collection task. The *data collection capacity* is defined as the average data receiving rate at the base station during a data collection process.

Interference Model: The available spectrum bandwidth for both the primary network and the secondary network is assumed to be $W = B/\tau$. Therefore, the upper bound of data collection capacity is W since the base station can receive at most one data packet during a time slot. In this paper, we take the *physical interference model* into account. At time t, suppose $\mathcal{S}_p^t$ (respectively, $\mathcal{S}_s^t$) is the set of all the PUs (respectively, SUs) trying to transmit data to some other PUs (respectively, SUs). For $\forall S_i \in \mathcal{S}_p^t$, assume its intended receiver is S_j. Then, S_j can successfully receive data from S_i at time t only if the Signal-to-Interference Ratio (SIR) at S_j associated with S_i satisfies

$$\frac{P_p \cdot D(S_i, S_j)^{-\alpha}}{\sum\limits_{S_k \in \mathcal{S}_p^t, S_k \neq S_i} P_p D(S_k, S_j)^{-\alpha} + \sum\limits_{s_k \in \mathcal{S}_s^t} P_s D(s_k, S_j)^{-\alpha}} \geq \eta_p,$$

where $D(\cdot,\cdot)$ is the Euclidean distance between two nodes, $\alpha > 2$ is the path loss exponent, and η_p is the threshold SIR value for the primary network. Similarly, for $\forall s_i \in \mathcal{S}_s^t$, assume its intended receiver is s_j. s_j can successfully receive data from s_i at time t only if the SIR at s_j associated with s_i satisfies

$$\frac{P_s \cdot D(s_i, s_j)^{-\alpha}}{\sum\limits_{S_k \in \mathcal{S}_p^t} P_p D(S_k, s_j)^{-\alpha} + \sum\limits_{s_k \in \mathcal{S}_s^t, s_k \neq s_i} P_s D(s_k, s_j)^{-\alpha}} \geq \eta_s,$$

where η_s is the threshold SIR value for the secondary network.

IV. Distributed Data Collection

In this section, we first construct a CDS-based data collection tree as the routing structure of data collection. Subsequently, we derive the Proper Carrier-sensing Range (PCR) for SUs. By working with the PCR, an Asynchronous Distributed Data Collection (ADDC) algorithm is proposed. ADDC can guarantee that the activities of PUs will not be interfered. Meanwhile, the SUs that transmit data simultaneously are also guaranteed to be interference-free. Finally, we theoretically analyze the performance of ADDC. It shows that ADDC can achieve order-optimal data collection capacity as centralized data collection algorithms [12][13][23][24] for traditional wireless networks.

A. Data Collection Tree

In ADDC, we take a CDS-based data collection tree as the routing infrastructure. For graph G_s, a *Dominating Set* (DS) of G_s is a subset U of V_s such that $\forall s_i \in V_s$, either $s_i \in U$ or s_i is adjacent to some node in U. If the induced subgraph of G_s on U is connected, then U is called a *Connected Dominating Set* (CDS). Since CDS is a good candidate for the connected *virtual backbone* of a wireless network, it has attracted a lot of research interests.

We use the method proposed in [25] to construct a CDS-based data collection tree. Taking the secondary network shown in Fig. 2 (a) as an example, the construction process can be done in three steps as follows. First, make a *Breadth First Search* (BFS) starting from the base station s_b, and identify a *Maximal Independent Set* (MIS) $\mathcal{D}$ of G_s. The nodes in the MIS are called *dominators* (evidently, the base station is also a dominator). As shown in Fig. 2 (b), the set of all the black nodes is the dominator set $\mathcal{D}$ of the secondary network in Fig. 2 (a). Second, find a set $\mathcal{C}$ consisting of *connectors* to connect the dominators in $\mathcal{D}$ to form a CDS. For example, in Fig. 2 (c), the set of blue nodes is the connector set. Finally, the nodes in $V_s \setminus (\mathcal{C} \cup \mathcal{D})$ are identified as *dominatees*. By choosing a dominator node for each dominatee in its 1-hop neighborhood as its parent node, we can construct a CDS-based data collection tree as shown in Fig. 2 (d).

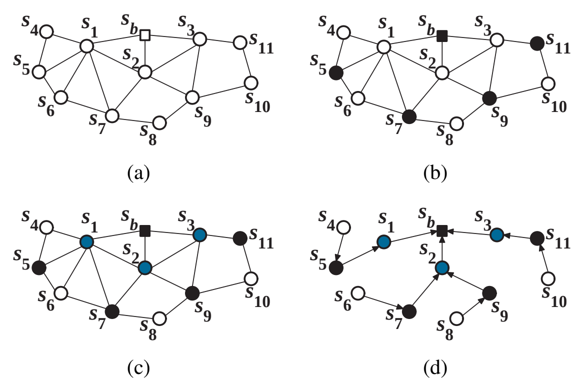


Figure 2. The construction of a CDS-based data collection tree. s_b is the base station. The black nodes in (b) are *dominators*, the blue nodes in (c) are *connectors*, and the white nodes in (c) are *dominatees*.

For the constructed CDS-based data collection tree, it has several interesting properties as shown in Lemma 1 [25].

Lemma 1: For $\forall s_i \in \mathcal{D}$, s_i is adjacent to at most 12 connectors, among which one is s_i's parent node if $s_i \neq s_b$.

B. Proper Carrier-sensing Range

In our proposed distributed data collection algorithm, all the SUs have to carrier-sense the spectrum to obtain a spectrum opportunity. Therefore, we need to study how to properly set the carrier-sensing range with the objectives: (i) the secondary network does not cause unacceptable interference to the activities of the primary network; (ii) all the SUs transmitting data simultaneously are interference-free; and meanwhile (iii) the carrier-sensing range is as small as possible, which implies SUs can obtain more spectrum opportunities. We have the following definitions.

Definition 4.1: **Concurrent Set.** $\mathbb{C} = \{u : u \in V_p \cup V_s\}$ is a concurrent set if all the nodes in $\mathbb{C}$ can carry out data transmissions simultaneously and successfully during a time slot.

The definition of a concurrent set implies that all the SUs in $\mathbb{C}$ have spectrum opportunities, and the activities of all the SUs and PUs in $\mathbb{C}$ are interference-free.

Definition 4.2: **$\mathcal{R}$-Set.** For $\mathcal{R} > 0$, $\mathbb{C} = \{u : u \in V_p \cup V_s\}$ is an $\mathcal{R}$-set if $\forall u, v \in \mathbb{C}$, $u \neq v$, then $D(u, v) \geq \mathcal{R}$.

Definition 4.3: **Proper Carrier-sensing Range (PCR).** $\mathcal{R}$ is a PCR if any $\mathcal{R}$-set is a concurrent set.

Now, we derive the conditions on PCR for SUs. To this end, we have two constraints. The first one is to guarantee the SUs will not cause unacceptable interference to the primary network, which is stated in Lemma 2. The second one is all the SUs that transmit data simultaneously are interference-free, which can be satisfied as shown in Lemma 3.

Lemma 2: Let $\mathbb{C} = \{u : u \in V_p \cup V_s\}$ be any $\mathcal{R}$-set. Assume all the nodes in $\mathbb{C}$ initiate data transmissions simultaneously. Then, to guarantee SUs will not cause unacceptable interference to PUs, it is sufficient to have the PCR

$$\mathcal{R} \geq (1 + \sqrt[\alpha]{\frac{c_2 \eta_p}{c_1}}) \cdot R, \tag{1}$$

where $c_1 = \frac{P_p}{\max\{P_p, P_s\}}$ and $c_2 = 6 + 6(\frac{\sqrt{3}}{2})^{-\alpha}(\frac{1}{\alpha-2} - 1)$.

Proof: For $\forall u \in \mathcal{C} \cap V_p$, let u' be its corresponding receiver. Then, to guarantee the data transmission from an arbitrary $S_i \in \mathbb{C}$ to S_i', we have

$$\frac{P_p \cdot D(S_i, S_i')^{-\alpha}}{\sum\limits_{S_k \in \mathbb{C}, S_k \neq S_i} P_p D(S_k, S_i')^{-\alpha} + \sum\limits_{s_k \in \mathbb{C}} P_s D(s_k, S_i')^{-\alpha}} \geq \eta_p.$$

Since $D(S_i, S_i')$ is the distance between S_i and S_i', $D(S_i, S_i') \leq R$, which implies $D(S_i, S_i')^{-\alpha} \geq R^{-\alpha}$. Furthermore,

$$\sum_{S_k \in \mathbb{C}, S_k \neq S_i} P_p \cdot D(S_k, S_i')^{-\alpha} + \sum_{s_k \in \mathbb{C}} P_s \cdot D(s_k, S_i')^{-\alpha} \tag{2}$$

$$\leq \sum_{U \in \mathbb{C}, U \neq S_i} \max\{P_p, P_s\} \cdot D(U, S_i')^{-\alpha} \tag{3}$$

$$= \max\{P_p, P_s\} \cdot \sum_{U \in \mathbb{C}, U \neq S_i} D(U, S_i')^{-\alpha}. \tag{4}$$

To obtain the upper bound of $\sum\limits_{U \in \mathbb{C}, U \neq S_i} D(U, S_i')^{-\alpha}$, for every $v \in \mathbb{C}$, we abstract the communication pair/link (v, v') to a node denoted by $\overline{v}$. In addition, for any $\mathcal{R}$-set, the densest packing is the *hexagon packing* as shown in Fig. 3. Then, all the nodes in $\mathbb{C}$ can be layered with respect to $\overline{S_i}$. By mathematical induction, it can be proven that the number of nodes in the l-th layer is at most $6l$ and the distance from $\overline{S_i}$ to any node at the l-th layer is at least $\frac{\sqrt{3}}{2} l \cdot F$ $(l \geq 2)$, where $F = \mathcal{R} - R$ (since for $\forall v, w \in \mathbb{C}$, $D(v, w) \geq \mathcal{R}$, therefore, $D(v, w') \geq \mathcal{R} - R$).

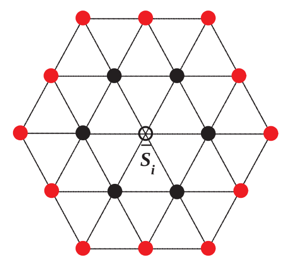


Figure 3. Hexagon packing with respect to $\overline{S_i}$. The black (respectively, red) nodes are the nodes at the first (respectively, second) layer.

Hence, we have

$$\sum_{U \in \mathbb{C}, U \neq S_i} D(U, S_i')^{-\alpha} \tag{5}$$

$$\leq 6F^{-\alpha} + \sum_{l \geq 2} 6l(\frac{\sqrt{3}}{2} lF)^{-\alpha} \tag{6}$$

$$= 6F^{-\alpha} + 6(\frac{\sqrt{3}}{2} F)^{-\alpha} \cdot \sum_{l \geq 2} l^{-\alpha+1} \tag{7}$$

$$\leq 6F^{-\alpha} + 6(\frac{\sqrt{3}}{2} F)^{-\alpha} \cdot (\zeta(\alpha - 1) - 1) \tag{8}$$

$$\leq 6F^{-\alpha} + 6(\frac{\sqrt{3}}{2} F)^{-\alpha} \cdot (\frac{1}{\alpha - 2} - 1) \tag{9}$$

$$= (6 + 6(\frac{\sqrt{3}}{2})^{-\alpha}(\frac{1}{\alpha - 2} - 1)) \cdot F^{-\alpha}. \tag{10}$$

Inequality (8) comes from the fact that $\sum\limits_{l \geq 1} l^{-\alpha+1}$ is a particular case of the *Riemann zeta function* $\zeta(\cdot)$ with parameter $\alpha - 1$. Inequality (9) is based on $\zeta(x) \leq \frac{1}{x-1}$. Let $c_1 = \frac{P_p}{\max\{P_p, P_s\}}$ and $c_2 = 6 + 6(\frac{\sqrt{3}}{2})^{-\alpha}(\frac{1}{\alpha-2} - 1)$. Then, we have

$$\frac{P_p \cdot D(S_i, S_i')^{-\alpha}}{\sum\limits_{S_k \in \mathbb{C}, S_k \neq S_i} P_p \cdot D(S_k, S_i')^{-\alpha} + \sum\limits_{s_k \in \mathbb{C}} P_s \cdot D(s_k, S_i')^{-\alpha}} \tag{11}$$

$$\geq \frac{c_1 R^{-\alpha}}{c_2 F^{-\alpha}}. \tag{12}$$

Therefore, to guarantee the data transmission from S_i to S_i', it is sufficient to have

$$\frac{c_1 R^{-\alpha}}{c_2 F^{-\alpha}} \geq \eta_p \Leftrightarrow F \geq \sqrt[\alpha]{\frac{c_2 \eta_p}{c_1}} \cdot R \tag{13}$$

$$\Leftrightarrow \mathcal{R} \geq (1 + \sqrt[\alpha]{\frac{c_2 \eta_p}{c_1}}) \cdot R. \tag{14}$$

Note that S_i is arbitrarily chosen in $\mathbb{C} \cap V_p$, this lemma holds. □

Lemma 3: Let $\mathbb{C} = \{u : u \in V_p \cup V_s\}$ be any $\mathcal{R}$-set. Assume all the nodes in $\mathbb{C}$ initiate data transmissions simultaneously. Then, to guarantee every SU in $\mathbb{C} \cap V_s$ can conduct data transmission successfully (*i.e.* every SU in $\mathbb{C} \cap V_s$ has a spectrum opportunity and all the SUs transmit data without interference), it is sufficient that

$$\mathcal{R} \geq (1 + \sqrt[\alpha]{\frac{c_2 \eta_s}{c_3}}) \cdot r, \tag{15}$$

where $c_3 = \frac{P_s}{\max\{P_p, P_s\}}$.

Proof: By the similar technique as in Lemma 2, this lemma can be proven. □

Let

$$\kappa = \max\{(1 + \sqrt[\alpha]{\frac{c_2 \eta_p}{c_1}}) \cdot \frac{R}{r}, 1 + \sqrt[\alpha]{\frac{c_2 \eta_s}{c_3}}\}. \tag{16}$$

From Lemma 2 and Lemma 3, if we set the PCR $\mathcal{R} = \kappa \cdot r$, then any $\mathcal{R}$-set is a concurrent set. Consequently, we set $\mathcal{R} = \kappa \cdot r$ in the following of this paper. We further show the PCR values under different situations in Fig. 4. From Fig. 4, we can see that the PCR value is bigger when $\alpha = 3.0$ than that of $\alpha = 4.0$. This is because a larger path loss exponent implies a transmitter induces less interference on other ongoing data transmissions. Additionally, $\mathcal{R}$ is a non-decrease function with respect to P_p, P_s, η_p, and η_s. This can also be seen from Lemma 2 and Lemma 3.

C. Data Collection Algorithm

Based on the constructed data collection tree and the PCR $\mathcal{R}$, we propose an *Asynchronous Distributed Data Collection* (ADDC) algorithm (Algorithm 1). In Algorithm 1, τ_c is the time duration of the *contention window* and $\tau_c < \tau$. We assume no two SUs located within each other's PCR having their backoff timers expired at the exactly same time[2].

Algorithm 1: The ADDC Algorithm

input : CDS-based data collection tree, $\mathcal{R}$
output: a distributed data collection plan
1 s_i $(1 \leq i \leq n)$ sets its carrier sensing range to $\mathcal{R} = \kappa \cdot r$;
2 **while** *s_i has some data for transmission* **do**
3   s_i randomly and uniformly chooses a value $t_i \in (0, \tau_c]$ as its backoff timer;
4   **while** *the backoff timer does not expire* **do**
5   s_i keeps sensing the spectrum with $\mathcal{R}$;
6   **if** *during a time slot, there is a PU or SU transmitting some data within its PCR,* i.e. *s_i does not have a spectrum opportunity or might cause interference to other active SUs* **then**
7   s_i freezes its backoff timer (stopping the countdown process) until the spectrum becomes free;
8   **if** *the spectrum is free* **then**
9   s_i's backoff timer continues the countdown process;
10   **if** *the backoff timer expires* **then**
11   s_i transmits one data packet to its parent node when a spectrum opportunity appears;
12   s_i waits for time $\tau_c - t_i$ before it starts another transmission activity;

In Algorithm 1, each SU sets its carrier-sensing range to $\mathcal{R}$ in line 1. In lines 2-12, the data transmission process of one data packet is described. In line 3, the backoff timer of s_i is set. Subsequently, s_i senses the spectrum (line 5). If the spectrum is busy, s_i stops the countdown process (lines 6-7). Otherwise, the countdown process of s_i's backoff timer continues (lines 8-9). If the backoff timer expires, s_i carries out a data transmission when a spectrum opportunity appears (line 11). Since we assume SUs within each other's PCR will not have their timer expired at the same time instant, line 11 can be accomplished without interference. Taking fairness into consideration, *i.e.*, to avoid s_i always occupying the spectrum, we still let s_i wait for time $\tau_c - t_i$ after it transmits the current data packet (line 12). This can also be proven in Theorem 1 (Section IV-D).

D. Performance Analysis of ADDC

In this subsection, we analyze the delay and capacity performance of ADDC. In our analysis, since τ_c is very small compared with the waiting time for a spectrum opportunity and the data transmission time, we ignore the delay induced by the backoff time. Actually, considering the backoff time only introduces a constant factor to the delay and capacity of ADDC.

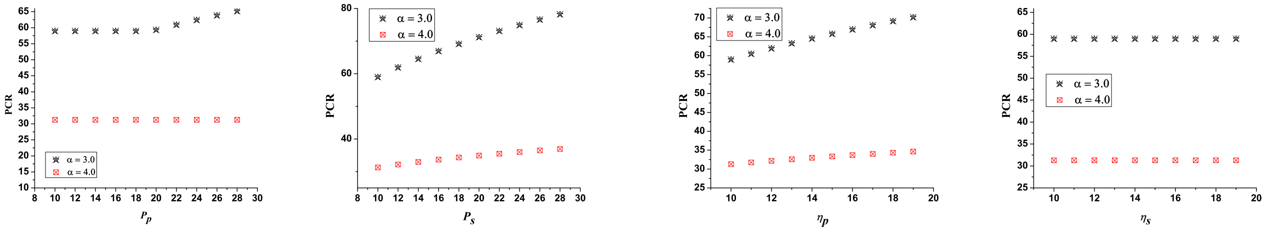
First, we introduce a geometric property of disk packing as follows.

Lemma 4: [25] Assume that $\mathfrak{D}$ is a disk of radius r_d and $\mathfrak{M}$ is a set of points with mutual distance of at least 1. Then,

$$|\mathfrak{D} \cap \mathfrak{M}| \leq \frac{2\pi r_d^2}{\sqrt{3}} + \pi r_d + 1, \tag{17}$$

where $|\cdot|$ is the cardinality of a set.

[2]Collisions due to simultaneous countdown-to-zero can be tackled by an exponential backoff mechanism in which the transmission probability of each SU is adjusted in a dynamic way based on the network business [22].



(a) PCR vs. P_p (b) PCR vs. P_s (c) PCR vs. η_p (d) PCR vs. η_s

Figure 4. The PCR value. The default settings are $\alpha = 4$, $P_p = 10$, $R = 12$, $\eta_p = 10$dB, $P_s = 10$, $r = 10$, and $\eta_s = 10$dB.

From Lemma 4, we can derive the following lemma, which states the number of dominators and connectors within the PCR of an SU in Algorithm 1. The proof of Lemma 5 is omitted due to space limitation.

Lemma 5: In Algorithm 1, the number of dominators and connectors within the PCR of an SU is upper bounded by $\beta_\kappa + 12\beta_{\kappa+1}$, where β_x is a function on x with $\beta_x = \frac{2\pi x^2}{\sqrt{3}} + \pi x + 1$.

Based on Lemma 5 and applying the Chernoff bound, we can obtain the upper bound of the number of SUs within the PCR of an SU as shown in Lemma 6. The proof of Lemma 6 is omitted due to space limitation.

Lemma 6: In Algorithm 1, the number of SUs within the PCR of an SU is upper bounded by $\Delta\beta_\kappa + 12\beta_{\kappa+1}$, where Δ is the maximum degree of the CDS-based data collection tree and $\Delta \leq \log n + \frac{\pi r^2(e^2-1)}{2c_0}$ with probability 1.

An SU obtains a spectrum opportunity only when no ongoing data transmission is initiated by any PU within its PCR during a time slot. Consequently, we show the expected waiting time and probability of a spectrum opportunity appearance for an SU in Lemma 7. The proof of Lemma 7 is omitted due to space limitation.

Lemma 7: To obtain a spectrum opportunity, the expected waiting time for an SU in Algorithm 1 is τ/p_o, where $p_o = (1-p_t)^{\pi(\kappa r)^2 N/c_o n}$ is the expected probability that an SU has a spectrum opportunity during a time slot.

Based on Lemma 7, we assume the waiting time for an SU is τ/p_o before a spectrum opportunity appears. Therefore, the results we obtained in the following are from the view of expectation. From Lemma 6 and Lemma 7, we have Theorem 1, which states the upper bound of the waiting time for an SU to transmit one data packet.

Theorem 1: In Algorithm 1, any SU having data for transmission can transmit at least one data packet to its parent node within time $(2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$.

Proof: For convenience, we first assume the secondary network is a stand-alone network[3]. For an arbitrary SU s_i, assume s_j is another arbitrary SU within s_i's PCR. We try to prove that "$\mathfrak{P}$: if s_i and s_j are competing for the spectrum, then, before s_i obtains the spectrum to transmit one data packet, s_j can transmit at most two data packets".

Assume both s_i and s_j have multiple data packets for transmission. During the x-th time slot in terms of s_i's time scale, s_i's backoff timer is set to $t_i \in (0, \tau_c]$. During the y-th time slot in terms of s_j's time scale, s_j's backoff timer is set to $t_j \in (0, \tau_c]$. Evidently, if the x-th time slot has no overlap with the y-th time slot as shown in Fig. 5 (a), then s_i and s_j are not competing for the spectrum at this moment. Therefore, we only have to prove $\mathfrak{P}$ when the x-th time slot of s_i has some overlap with the y-th time slot of s_j.

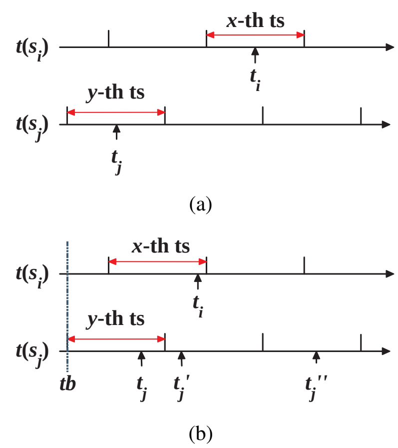


Figure 5. The transmission order of s_i and s_j, where $t(s_i)$ and $t(s_j)$ are the time scales of s_i and s_j respectively, ts = *time slot*, and tb = *time baseline*.

Without loss of generality, we assume t_j is before t_i as shown in Fig. 5 (b)[4], $t_i < (\tau_c - t_j) + \tau_c = 2\tau_c - t_j$. Take the start point of the y-th time slot as the *time baseline* (starting time). Then, according to Algorithm 1, s_j transmits a data packet at time t_j and sets its next backoff timer as $\varepsilon_1 \in (0, \tau_c]$ after waiting for time $\tau_c - t_i$, *i.e.* s_j will transmit the second data packet at time $t_j' = \tau_c + \varepsilon_1$. Since $t_i < 2\tau_c - t_j$, it is still possible that $t_j' < t_i$ as shown in Fig. 5 (b). Similarly,

[3]Here, a stand-alone secondary network means the primary network does not exist or is not working, which implies all the SUs always have spectrum opportunities.

[4]For the case that t_i is before t_j, it is clearly s_i will transmit one data packet before s_j according to Algorithm 1. Then, $\mathfrak{P}$ is true.

after transmitting the second data packet, s_j waits for time $\tau_c - \varepsilon_1$ and sets its backoff timer as ε_2, *i.e.* s_j will transmit the third data packet at time $t''_j = 2\tau_c + \varepsilon_2$. Now, since $t''_j = 2\tau_c + \varepsilon_2 > 2\tau_c > t_i$ as shown in Fig. 5 (b), s_i will transmit one data packet before s_j transmits the third data packet. Then, $\mathfrak{P}$ is true.

Because s_i and s_j in $\mathfrak{P}$ are arbitrarily chosen, and at most $\Delta\beta_\kappa + 12\beta_{\kappa+1} - 1$ SUs are within the PCR of an SU according to Lemma 6, we conclude that every SU with data for transmission can transmit at least one packet to its parent node within $2(\Delta\beta_\kappa + 12\beta_{\kappa+1} - 1) + 1 = 2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1$ time slots. Now, we remove the assumption that the secondary network is a stand-alone network. Based on Lemma 7, the expected time consumption for each SU to transmit one data packet is upper bounded by $(2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$. □

From Theorem 1, we can see that Algorithm 1 also takes fairness into consideration when it collects data. Furthermore, the following corollary can be obtained straightforwardly.

Corollary 1: The expected time to collect all the data packets from $V_s \setminus (\mathcal{D} \cup \mathcal{C})$ to $\mathcal{D} \cup \mathcal{C}$ is upper bounded by $(2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$.

By the similar technique in the proof of Theorem 1, we can obtain the following lemma, which states the waiting time for an SU in $\mathcal{D} \cup \mathcal{C}$ to successfully transmit a data packet.

Lemma 8: After all the packets at $V_s \setminus (\mathcal{D} \cup \mathcal{C})$ have been collected to $\mathcal{D} \cup \mathcal{C}$, the expected time of an SU in $\mathcal{D} \cup \mathcal{C}$ to transmit a data packet to its parent node is upper bounded by $(2\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$.

Proof: After all the packets at $V_s \setminus (\mathcal{D} \cup \mathcal{C})$ have been collected to $\mathcal{D} \cup \mathcal{C}$, only the SUs in $\mathcal{D} \cup \mathcal{C}$ may have data packets for transmission. From Lemma 5, there are at most $\beta_\kappa + 12\beta_{\kappa+1} - 1$ dominator and connector SUs within the PCR of an SU in $\mathcal{D} \cup \mathcal{C}$. From the proof of Theorem 1, this lemma can be proven. □

Then, based on Corollary 1 and Lemma 8, the following theorem can be proven, which shows the delay and capacity performance of ADDC.

Theorem 2: The expected delay induced by ADDC is upper bounded by $O((2\beta_\kappa + 24\beta_{\kappa+1} - 1)n\tau/p_o)$. This implies the achievable data collection capacity of ADDC is $\Omega(\frac{p_o}{2\beta_\kappa + 24\beta_{\kappa+1} - 1} \cdot W)$, which is order-optimal.

Proof: From Corollary 1, the expected time to collect data packets from $V_s \setminus (\mathcal{D} \cup \mathcal{C})$ to $\mathcal{D} \cup \mathcal{C}$ is upper bounded by $(2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$. Meanwhile, the base station also collects at least Δ_b data packets from its children, where Δ_b is the degree of s_b in the data collection tree. After that, the base station can receive at least one data packet every $(2\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o$ time according to Lemma 8. In summary, the time consumption of ADDC is upper bounded by $(2\Delta\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o + (n - \Delta_b)(2\beta_\kappa + 24\beta_{\kappa+1} - 1)\tau/p_o = O((2\beta_\kappa + 24\beta_{\kappa+1} - 1)n\tau/p_o)$. Therefore, the achievable data capacity of ADDC is lower bounded by $\frac{n \cdot B}{O((2\beta_\kappa + 24\beta_{\kappa+1} - 1)n\tau/p_o)} = \Omega(\frac{p_o}{2\beta_\kappa + 24\beta_{\kappa+1} - 1} \cdot W)$. Since the upper bound of data collection capacity is W, the achievable capacity of ADDC is order-optimal. □

From Theorem 2, the proposed ADDC successfully achieves order-optimal data collection capacity even working in a distributed and asynchronous manner. Compared with the existing order-optimal centralized algorithms, ADDC is scalable and more practical for unstable and frequently changed CRNs.

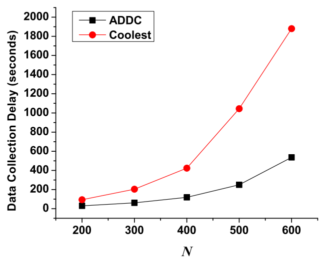
V. Simulation and Analysis

In this section, we validate the performance of the proposed ADDC via simulations. In all the simulations, we consider a secondary network consisting of n SUs and a base station coexisted with a primary network consisting of N PUs. Both of the networks are *i.i.d.* in a square area with size A. All the SUs and PUs share the same time, space, and spectrum and SUs cannot cause any unacceptable interference to PUs. The network time is assumed to be slotted and the time duration of a time slot is 1 millisecond (ms). During a time slot, each PU initiates a data transmission with probability p_t or keeps silent with probability $1 - p_t$. In addition, the propagation time of a data packet (no matter produced by a PU or SU) is less than 1 ms. For other system parameters, *e.g.* A, α, N, P_p, R, η_p, p_t, n, P_s, r, η_s, and *etc* (which have the same meanings as defined before), we will specify them in each group of simulations (see Fig. 6).

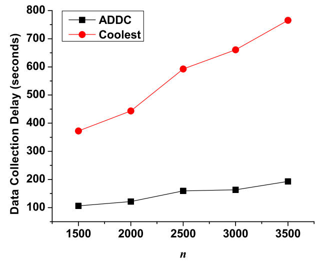
In the simulations, we use ADDC to denote our proposed asynchronous and distributed data collection algorithm for CRNs. In ADDC, the contention window τ_w is assumed be 0.5 millisecond. Since there is no existing data collection algorithm for CRNs currently to the best of our knowledge, we compare ADDC with the most recently published routing algorithm for CRNs (necessary modification is required), denoted by Coolest [17]. In Coolest, the path with the most balanced and/or the lowest spectrum utilization by PUs is preferred for a data transmission. To finish a data collection task, in Coolest, we assume each SU of the secondary network produces a data packet that will be transmitted to the base station. In the following, each group of simulations is repeated for 10 times and the results are the average values.

A. Data Collection Delay vs. Network Size (N and n)

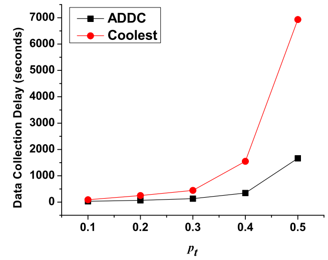
When we change the number of PUs or SUs in a CRN, the changes of data collection delay of ADDC and Coolest are shown in Fig. 6 (a) and (b), respectively. From Fig. 6 (a) and (b), we can see that when the number of PUs N and the number of SUs n increase, the induced data collection delay of both ADDC and Coolest increases. This is because (i) more PUs implies more data transmission activities of the primary network (the default $p_t = 0.3$), which further implies an SU has to wait longer for a spectrum opportunity; and (ii) when n increases, the traffic



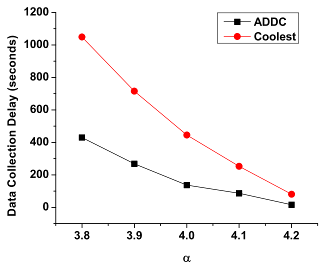
(a) Data collection delay vs. N



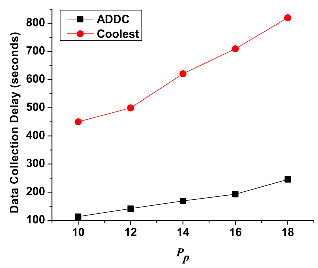
(b) Data collection delay vs. n



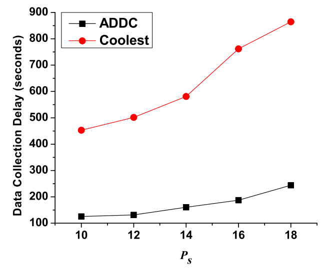
(c) Data collection delay vs. p_t



(d) Data collection delay vs. α



(e) Data collection delay vs. P_p



(f) Data collection delay vs. P_s

Figure 6. Data collection delay of ADDC and Coolest. The default settings are $A = 250 \times 250$, $\alpha = 4$, $N = 400$, $P_p = 10$, $R = 10$, $\eta_p = 8$dB, $p_t = 0.3$, $n = 2000$, $P_s = 10$, $r = 10$, and $\eta_s = 8$dB.

of a data collection task becomes heavier, *i.e.* the data communication in the secondary network becomes more crowded. It follows that more data collection delay is induced. ADDC has a better performance than that of Coolest. This is because ADDC takes a distributed data collection manner with fairness consideration, which can reduce the data accumulation effect and enable as many SUs as possible to transmit data simultaneously. On the other hand, since Coolest prefers the path with the most balanced and/or the lowest spectrum utilization by PUs, many SUs might choose the same path. This will make the data accumulation effect more serious. From Fig. 6 (a) and (b), we can also see that the increase trend in Fig. 6 (a) is much faster than Fig. 6 (b). This demonstrates that the waiting time for spectrum opportunities is the majority in the overall data collection delay. On average, ADDC induces 266% and 282% less delay compared with Coolest, respectively.

B. Data Collection Delay vs. p_t and α

The impact of p_t (the probability of a PU to initiate a data transmission during a time slot) on data collection delay of ADDC and Coolest is shown in Fig. 6 (c). From Fig. 6 (c), when p_t increases, the induced data collection delay of both ADDC and Coolest increases very fast. This is because the spectrum opportunities for SUs decrease fast with the increase of p_t, *i.e.* more activities of the primary network. The impact of the path loss exponent α on the data collection delay of ADDC and Coolest is shown in Fig. 6 (d). When α increases, the interference induced by a transmitter to other ongoing transmissions decreases. Therefore, SUs might have more spectrum opportunities and more SUs can conduct data transmissions concurrently without interference. It follows that the delay of both ADDC and Coolest decreases. Again, as shown in Fig. 6 (c) and (d), ADDC has a better performance than Coolest. On average, ADDC takes 314% and 171% less time than Coolest to finish a data collection task in Fig. 6 (c) and (d), respectively.

C. Data Collection Delay vs. Transmission Power (P_p and P_s)

The impacts of P_p (power of PUs) and P_s (power of SUs) on the performance of ADDC and Coolest are shown in Fig. 6 (e) and (f), respectively. From Fig. 6 (e) and (f), we can see that when P_p and P_s increase, the induced delay of both ADDC and Coolest increases. This is because a large working power will cause more interference to other transmissions. Therefore, the spectrum opportunities are reduced and less SUs can conduct data transmissions simultaneously. Because of the same reasons stated before, ADDC finishes a data collection task much faster than Coolest. On average, it takes ADDC 260% and 273% less time to finish a data collection task compared with Coolest as shown in Fig. 6 (e) and (f), respectively.

VI. Conclusion

Cognitive Radio Networks (CRNs) introduce a novel promising communication paradigm for the future, where SUs can opportunistically access unused licensed spectrum without harming the communications among PUs. In this paper, we study the distributed data collection problem for asynchronous CRNs. First, we study how to set a Proper Carrier-sensing Range (PCR) for SUs. Subsequently, based on the derived PCR, we propose an Asynchronous Distributed Data Collection (ADDC) algorithm for CRNs with fairness consideration. Through theoretical analysis, we show that ADDC successfully achieves order-optimal delay and capacity, which implies ADDC is scalable and practical. Finally, the simulation results demonstrate that ADDC can effectively accomplish a data collection task and significantly reduce delay.

Acknowledgment

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