Ad Hoc Networks 56 (2017) 186–201

Contents lists available at ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

Opportunistic network coding for secondary users in cognitive radio networks

Yuben Qu[a,b,*], Chao Dong[a], Shaojie Tang[c], Chen Chen[a], Haipeng Dai[d], Hai Wang[a], Chang Tian[a]

[a] College of Communications Engineering, PLAUST, No. 88 Houbiaoying, Yudao Street, Qianhuai District, Nanjing, Jiangsu 210007, China
[b] Department of Information Engineering, Rocket Force University of Engineering, No. 2 Tongxin, Hongqing Zhen, Baqiao District, Xi'an, Shao'xi 710025, China
[c] Naveen Jindal School of Management, University of Texas at Dallas, 800 W. Campbell Road, Richardson, Texas, USA
[d] Department of Computer Science and Technology, Nanjing University, No. 22 Hankou, Gulou District, Nanjing, Jiangsu 210000, China

ARTICLE INFO

Article history:
Received 29 June 2015
Revised 7 October 2016
Accepted 22 December 2016
Available online 30 December 2016

Keywords:
Network coding
Cognitive radio networks
Multicast
Multi-armed bandits

ABSTRACT

In cognitive radio networks (CRNs), secondary users (SUs) may employ network coding to pursue higher throughput. However, as SUs must vacate the spectrum when it is accessed by primary users (PUs), the available transmission time of SUs is usually uncertain, i.e., SUs do not know how long the idle state can last. Meanwhile, existing network coding strategies generally adopt a block-based transmission scheme, which means that all packets in the same block can be decoded simultaneously only when enough coded packets are collected. Therefore, the gain brought by network coding may be dramatically decreased as the packet collection process may be interrupted due to the unexpected arrivals of PUs.

In this paper, for the first time, we develop an efficient network coding strategy for SUs while considering the uncertain idle durations in CRNs. At its heart is that systematic network coding (SNC) is employed to opportunistically utilize the idle duration left by PUs. To handle the uncertainty of idle durations, we utilize confidential interval estimation to estimate the expected duration for stochastic idle durations, and multi-armed bandits to determine the duration sequentially for non-stochastic idle durations, respectively. Then, we propose a coding parameter selection algorithm for SNC by considering the complicated correlation among the receptions at different receivers. Simulation results show that, our proposed schemes outperform both traditional optimal block-based network coding and non-network coding schemes, and achieve competitive performance compared with the scheme with perfect idle duration information.

1. Introduction

Due to the pressing demand of efficient frequency spectrum usage, cognitive radio networks (CRNs) have spurred a wide range of research interests because they can improve spectrum utilization of the limited spectrum resources [1]. The key idea in CRNs is to allow *secondary users* (SUs) share the spectrum simultaneously with the *primary users* (PUs), as long as they do not harm the transmissions of PUs [2]. As a result, a critical challenge for SUs in CRNs is how to efficiently utilize the "scarce opportunities" for higher performance.

In recent years, network coding [3] has emerged as a promising technology to achieve higher performance in wireless networks. By combining multiple input packets into one packet algebraically before forwarding, network coding is able to achieve the multicast capacity [3]. Due to its huge benefits, network coding is not only applied in multi hop scenarios, but also in single hop broadcast scenarios, which has been extensively studied in [4–7], etc. Intuitively, network coding can also be utilized to improve SUs' performance, e.g., the efficiency of SUs utilizing the "scarce opportunities" may be greatly increased.

Network coding has the potential to improve SUs' performance in CRNs. However, it is not easy to extend the previous studies of network coding to SUs in CRNs. To begin with, network coding usually adopts a block-based transmission (e.g., [8–10], etc). That is, the data packets in the same block can be recovered only when at least the number of block size coded packets are collected at the receivers. The block size must be carefully predetermined according to the current available time, since the block size is directly related to the throughput gain [10]. However, in the context of CRNs,

* Corresponding author.
E-mail addresses: quyuben@gmail.com (Y. Qu), dch999@gmail.com (C. Dong).

http://dx.doi.org/10.1016/j.adhoc.2016.12.009
1570-8705/

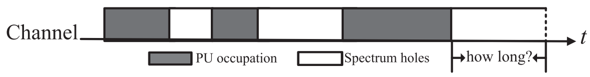


Fig. 1. The "spectrum holes" are limited and *uncertain*.

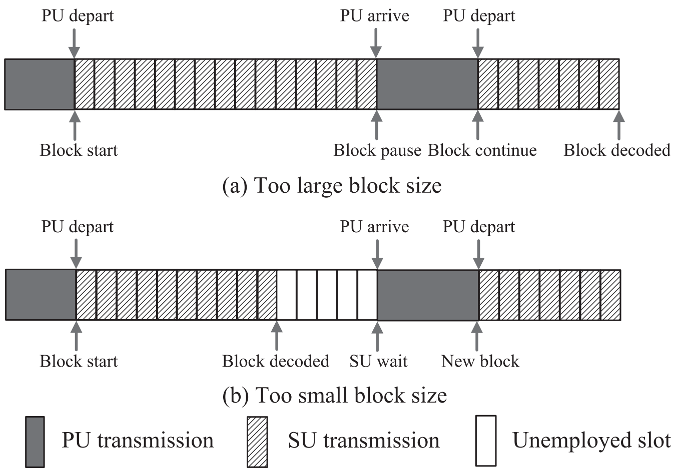


Fig. 2. The block size selection is challenging due to the *uncertain* idle duration.

SUs can only opportunistically explore the "spectrum holes" on PU channels for data transmissions. As shown in Fig. 1, these "spectrum holes", which are the available transmission time for SUs, are usually *uncertain* in the sense that SUs' transmissions may be interrupted by PUs at any time. Due to this uncertainty, it is challenging to apply network coding in SUs' data transmission.

Take Fig. 2 as an example. In Fig. 2(a), a block with too large size cannot be decoded in the current idle duration and have to be resumed in the next idle duration, which depends on the activity of PUs. Since the activity of PUs is uncertain and may be unpredictable sometimes, the packet delay (decoding & waiting) may be extremely large, which is unacceptable to delay-sensitive traffic. On the contrary, if the SUs choose a too small block size (see Fig. 2(b)), the block may be decoded long before the current idle duration ends. However, as put in [10], small block size cannot bring great throughput gains. Therefore, the coding scheme as well as the block size selection should be reconsidered and carefully designed with consideration of the uncertain idle durations in CRNs.

In this study, we aim to develop an efficient network coding scheme for SUs to achieve the promising performance gains in CRNs. *To our best, this is the first work to study how to leverage network coding to improve SUs' performance while considering the uncertain idle durations.* The key issue in the problem of network coding for SUs is to determine the block size k before each round of data transmission. According to [33–36], the optimal block size k^* is determined by several factors, among which a major one is the number of time slots I that is available for transmission. Thus, we propose to estimate I first, and then choose k^* based on the estimated I. Besides, to jointly consider the estimation of I and the selection of k^*, we employ systematic network coding (SNC) in the coded data transmission to reduce the negative effect from the inaccurate estimation.

To summarize, our main contributions are as follows.

1. We propose two idle duration selection algorithms for SUs to estimate the duration of available transmission. For the case where the idle duration is stochastic, we employ confidential interval estimation (CIE) to estimate the idle duration on average. For the non-stochastic case, we model the idle duration selection problem into a non-stochastic multi-armed bandits (MAB) problem [21] and propose a MAB-based algorithm to sequentially select the idle durations.
2. We develop a block size selection algorithm for SNC to adaptively determine the proportion of the number of coded packets and uncoded packets to be transmitted. We analytically show that the algorithm can be addressed in $O(NI^4)$ time, where N is the number of SU receivers and I is the estimated duration of available transmission.
3. We generalize our approach framework to incorporate multiple PU channels. To handle the uncertain idle durations under multiple PU channels, we discuss how to modify the CIE-based algorithm for stochastic idle durations and the MAB-based algorithm for non-stochastic idle durations, respectively. We also theoretically analyze the performance of the modified two-dimensional MAB algorithm.
4. Our simulation results show that, the gain of our proposed scheme over the non-network coding transmission policy and optimal random linear network coding scheme is up to 1.48× and 1.85× under stochastic idle durations, and 1.2× and 1.75× under non-stochastic idle durations, respectively. Besides, compared to the scheme with perfect idle duration information, our scheme achieves high steady utilization, around 90% for stochastic idle durations, and 88% for non-stochastic case, respectively.

The rest of this paper is organized as follows. The related work is reviewed in Section 2. Section 3 describes the model and problem formulation. In Section 4, we present two algorithms to handle the uncertainty of the available time for SUs, while a block size selection algorithm for SNC is developed in Section 5. Section 6 discusses how to extend our algorithms when there are multiple PU channels. The performance evaluation is conducted via extensive simulations in Section 7. Section 8 presents the discussion. Finally, Section 9 concludes the paper and discusses the future work.

2. Related work

The related studies can be generally categorized into the following four aspects: learning-based dynamic spectrum access in CRNs, characterization and modeling of PU behavior in CRNs, utilization of network coding in CRNs, and network coding for real-time traffic.

2.1. Learning-based dynamic spectrum access in CRNs

Our work is sort of learning the primary user environment in CRNs. There has been a rich body of studies on dynamic spectrum access in CRNs in existing works. SUs need to conduct a learning process to select good channels since channel availability and quality is unknown to SUs. Existing works study this problem from a sequential decision perspective by multi-armed bandits (MAB) approaches, or from a game theoretic perspective by equilibrium convergence.

Shu and Krunz [11] propose a throughput-optimal decision scheme for stochastic homogeneous channels. The proposed scheme uses a threshold to distinguish good channel and bad channel. For the case of pre-allocated ranks for SUs and non such prior information, Anandkumar et al. [12] proposes two distributed learning and allocation schemes respectively. Li et al. [13] studies the joint channel sensing, probing and accessing problem in CRNs when channel states are non-stochastic, and presents an almost throughput optimal scheme with the help of MAB.

Moreover, some works study dynamic spectrum access from an adaptive, game theoretic learning perspective. Maskery et al. [14] models the dynamic channel access problem as a non-cooperative game for stochastic homogeneous channels, and derives the probability of channel contention by CSMA mechanism.

For the case of heterogeneous channel, Xu et al. [15] develops a potential game to maximize the expected throughput of all SUs.

To sum up, current works on learning-based dynamic spectrum access in CRNs mainly focus on how to access the best channel that can boost the greatest throughput. However, after accessing the channel, how to efficiently transmit data packets in the limited and uncertain idle durations has not been studied, which is the main contribution of this paper. Furthermore, although MAB has been widely used in CRNs, these works generally adopt MAB for channel selection, while MAB is mainly used to choose the idle duration of the channel in our work.

2.2. Characterization and modeling of PU behavior in CRNs

In addition to learning the primary user environment in CRNs, there are rich studies about the characterization and modeling of PU behavior in CRNs. To understand the characteristics mainly including the variability in spectrum user over different types of areas in a metropolitan area, Palaios et al. [16] conducts measurements by three spectrum analyzers in London. They study the correlation structures and dynamics in spectrum use from the perspectives of temporal, spatial and frequency domains. Wellens et al. [17] investigates the effect of the spectrum occupancy statistics on the MAC-layer sensing performance, mainly from the temporary domain. They show that if the OFF- and ON-period durations tend to be longer, the adaptive algorithms exploiting knowledge on these distributions will achieve significant performance gains.

Moreover, Ghosh et al. [18] develops a novel spectrum occupancy model to generate accurate frequency and temporal behavior of various wireless transmissions. They employ the first- and second-order parameters in the statistical spectrum occupancy model by using statistical characteristics extracted from actual radio frequency measurements. Pagadarai et al. [19] shows that the variation in the spectrum occupancy at different locations within the same city is relatively high, and further utilizes a four-state Markov model that characterizes the time-varying behavior of the spectral occupancy of a particular channel. In a word, the above studies mainly focus on how to characterize and model the PU behavior in CRNs from different domains, while rarely considering the actual SUs' data transmissions, not to mention employing network coding for performance gains.

2.3. Utilization of network coding in CRNs

In related works on the utilization of network coding in CRNs, a large body of work has been carried out on exploiting the various possible benefits of network coding for CRNs from different angles. Jin et al. [20] studies multicast scheduling with cooperation and network coding in CRNs, mainly adopting network coding during the transmissions to reduce overhead and perform error control and recovery. Similarly, both Baldo et al. [23] and Asterjadhi et al. [25] use network coding to exchange reliable control information, which enables cognitive radios to maintain up-to-date information regarding the network status and thus improves performance. Using network coding as an assistance strategy, Almasaeid and Kamal [26] propose an algorithm to reduce the effect of the channel heterogeneity property on the multicast throughput in cognitive radio wireless mesh networks.

Network coding is viewed as a spectrum shaper to increase the spectrum availability and predictability for SUs, through exploiting network coding on PUs only [28–30]. Also, Huang et al. [27] investigates the capacity of a cognitive radio relay network, and shows that utilizing network coding to make primary resources available for a cognitive network through cooperative relaying is efficient and viable. Shu et al. [31] proposes a network coding-aware channel allocation and routing scheme for multi-hop CRNs, by taking advantage of network coding opportunities and channel availability in order to maximize the throughput performance. Besides, based on network coding, Geng et al. [24] proposes a novel approach for the minimum-energy multicast in CRNs to improve the throughput of the secondary network. Zhong et al. [32] presents a coding aware opportunistic routing protocol for multi-channel CRNs. However, [32] focuses on utilizing inter-session network coding for CRNs, while the network coding technique used in our work is attributed to intra-session network coding.

All in all, although network coding has been widely utilized in CRNs, few works consider utilizing network coding for SUs' data transmissions. Furthermore, previous studies seldom consider the uncertainty of the idle durations, which is a critical issue in the application of network coding for SUs.

2.4. Network coding for real-time traffic

The problem of network coding for SUs is similar to the problem of network coding for real-time traffic [33–37]. In the application of real-time traffic, every packet must be delivered to the receiver in a hard deadline; otherwise, it is useless. Therefore, for the sender, it should adjust the block size according to various deadlines. To address this problem, many block size adjustment algorithms are proposed. However, these algorithms cannot apply to our problem because these algorithms assume that the available transmission time is certain. In CRNs, the available transmission time for SUs is uncertain. Further, the uncertainty will greatly affect the performance of SUs as we will show in the simulations.

Moreover, to reduce the negative effect of the uncertainty, we propose to employ systematic network coding in the coded data transmission, while most of the aforementioned works utilize random linear network coding. Thus, our study is fundamentally different from the previous studies of network coding for real-time traffic.

To summarize, most existing studies ignore the fundamental issue that *how the SUs efficiently utilize network coding to improve performance, since the available transmission time for SUs is not just limited but also highly uncertain*. In contrast, our work takes a closer look to the utilization of network coding for SUs in CRNs, which leads to a promising achievable throughput performance.

3. Model & problem formulation

In this section, we will introduce the basic system and network model used in our work, and then present the problem formulation of network coding for SUs in CRNs.

3.1. System and network model

In this study, we consider the multicast service of SUs in single hop scenarios, which is a common service in CRNs [26,28,30]. Assume that there are only one PU channel in the network, and many SUs can opportunistically access the channel. Without loss of generality, we assume that there are $N + 1$ SUs, in which one SU is the sender, and the rest ones are receivers. For the SUs' application, any packet that cannot be delivered to all SU receivers is useless without contributing to the throughput. Obviously, the SUs need to sense the channel to determine whether it is idle or not before accessing the channel. We here assume that the time for sensing the status of the channel is proximately t_s on average.

In this work, we consider unreliable PU channels and assume that the reliability of the channel between the SU sender and receiver n is $1 - \varepsilon_n$. Each SU is equipped with two radios: one is a half-duplex cognitive radio for data transmissions, and the other

Table 1
A summary of key notations.

Notation	Definition
N	# of SU receivers
T	# of total rounds
$\mu_{\mathbb{N}}$	# of delivered packets over $\mathbb{N}$
k	# of uncoded packets to be sent
i_t	# of time slots determined by SUs at round t
k_t	Block size determined at round t
t_s	Average sensing time
I	Estimated idle duration
R	Real idle duration
$I_{\max}$	Maximum idle duration
ε_n	Channel loss rate between the SU sender and receiver n
$\prod$	Set of idle durations
$\mathbb{N}$	Set of SU receivers
S_n	Set of decoded packets at receiver n
$\phi(t)$	SUs' strategy at round t
α_t	SUs' decision to access the channel or not at round t
$g_\phi(t)$	Gain for strategy ϕ at round t
$G_s(T)$	Total gain over a fixed strategy s up to round T
$\hat{G}(T)$	Total gain over chosen strategies up to round T

is a half-duplex normal radio working on a common control channel (CCC) for control messages exchange [26,38]. Under this setting, time is slotted and synchronized among the system. We note that in our study, one time slot consists of both the time of channel sensing and the time of transmitting one data packet, which aims to reduce the interference to PUs as much as possible. In the SUs' side, to reduce feedback overhead, we allow each SU receiver to feedback when it can decode a block or at the end of the current idle duration. Table 1 provides a reference for the major notations used in this paper.

In the problem of network coding for SUs in CRNs, the SUs need to firstly estimate how long the idle state would last, and then determine the corresponding network coding strategy. We consider both the case when the idle duration of the PU channel is stochastic and the case when the idle duration is non-stochastic. In the former case, the idle duration follows some probability distribution but the exact distribution parameter may be unknown at the SUs. This stochastic characteristic could help estimating the idle duration on average. Comparatively, in the latter case, the idle duration may be arbitrarily changing and does not follow any probability distribution. In this case, without knowing the priori information of the PU channel, the SUs have to adopt a strategy for choosing the possible idle duration sequentially.

3.2. Problem formulation

The two issues in our problem are how to estimate the idle duration I and determine the coding parameter k based on the estimated I. We note that the former issue is affected by the uncertainty of the idle duration. And the latter one should be carefully considered by combining the characteristic of network coding. We will explain the issues one by one.

3.2.1. How to handle the uncertainty of the idle duration

When the activity of the PU is of regularity, the idle duration of the PU channel follows some probability distribution, e.g., exponential, geometric or log-normal [17,39,40], etc. Assume that the PU channel has idle durations drawn from a set $\Pi = \{i_1, i_2, ..., i_m, ...\}$ with $i_m < i_{m+1}$ for $m \in \{1, 2, \ldots\}$, following some distribution. Since the idle duration of the PU channel, i.e., I, follows some probability distribution, we may estimate the expectation of I, i.e., EI, based on historical statistics. Then we can use the estimate to decide for the block size selection process. The learning scheme for SUs can be described as follows. At the beginning, the SUs just "listen" multiple idle durations, so as to estimate the value of EI based on the previous data according to statistical methods such as confidence interval estimation. The number of sample idle durations needed mainly depends on the probability distribution type and the predetermined confidential level, which will be introduced in Section 4.1.

When the idle duration is non-stochastic, i.e., it does not follow any probability distribution. This sequential idle duration selection problem can be seen as a non-stochastic multi-armed bandits (MAB) problem [21]. Since there is no gain if no data is transmitted in one time slot, we exploit a block of continuous channel sensing time called as a *round* in our study. After a round, the SUs choose an idle duration, according to the sensing result and previous gains. The following immediate time slots spent for transmitting data are not counted in a round. The total data delivered in those transmission time slots is defined as the gain of the previous sensing round. Note that the chosen idle duration may exceed the real idle duration, so the transmission may be disrupted in advance due to the arriving PU. The explicit gain not only depends on the idle duration selection scheme, but also the transmission policy of the SUs, which will be discussed in the following section.

The strategy for sensing/choosing consists of many sequential rounds of sensing. A sensing/choosing strategy $\phi = <\alpha_t, i_t>$ by the SUs will decide its action. Suppose there exists a maximum of the idle duration, i.e., $I_{\max}$. At every round t, $\alpha_t \in \{0, 1\}$ denotes whether the SUs decide to access the channel or not, and $i_t \in \Phi \triangleq \{1, 2, ..., I_{\max}\}$ is the idle duration chosen. The value of α_t is determined according to the sensing result: $\alpha_t = 1$ if the channel is busy and $\alpha_t = 0$ otherwise. The value of i_t is selected by the MAB algorithm. Let $g_\phi(t)$ denote the gain of a strategy ϕ at round t. In practical, after each round, the SU sender will examine the performance of its strategy based on the ACK from the SU receivers. The value of $g_\phi(t)$ can be calculated as the total number of successful delivered packets during round t.

The accumulative gain up to round T of each strategy s is $G_s(T) = \sum_{t=1}^{T} g_s(t)$. And the total gain of all chosen strategies accumulating up to round T is $\hat{G}(T) = \sum_{t=1}^{T} g_{\phi_t}(t)$, where the strategy ϕ_t is the SUs' strategy at round t. ϕ_t is chosen randomly according to the determined probability distribution over Φ. The throughput can be defined as $H \triangleq \frac{\sum_{t=1}^{T} g_{\phi_t}(t)}{T'}$, where T' is the system lifetime. In this study, we aim to design a strategy that maximizes the expected throughput, i.e., $\max_\phi H$, under the lifetime constraint: $\sum_{t=1}^{T} m_t t_s + \sum_{t=1}^{T} \alpha_t i_t \le T'$, where $m_t t_s$ ($m_t \ge 1$) denotes the sensing time at round t.

Meanwhile, in MAB problems the performance is usually measured in terms of regret. In our application, the regret is the difference between the expected total number of delivered data packets using our proposed algorithm and that using the static optimal solution over lifetime T'.[1] The static optimal solution for the SU sender is the strategy j that achieves the maximum delivered data packets if the SUs keep using that strategy for all T rounds. Accordingly, we define the regret τ after T rounds of an online strategy ϕ_t as $\tau = \max_{j \in \Phi} G_j(T) - \hat{G}(T)$. A strategy, whose average regret per round $\tau/T' \to 0$ with probability 1 when $T' \to \infty$, is a zero-regret strategy. Our objective is thus to design a strategy ϕ with small regret.

3.2.2. How to effectively utilize network coding for SUs' transmission

After determining an idle duration, e.g., I, the SUs begin to transmit data by network coding over the channel.

In this study, we focus on systematic network coding (SNC) [22] to improve the throughput performance of SUs. SNC is a special case of random linear network coding (RLNC) [41]. Under

[1] If the lifetime is fixed, the maximum data packets delivered means the maximum throughput achieved.

RLNC, all packets sent by the sender are coded packets, and the receivers can recover all original packets in the block simultaneously only after receiving enough coded packets. Comparatively, under SNC, both coded packets and uncoded packets are sent. Obviously, uncoded packets can also be seen as a special version of coded packets, i.e., only one of the coding coefficients is non-zero.

Compared to RLNC, SNC can reduce the per-packet delay without reducing the throughput. This is because some receivers can still obtain several data packets by successfully receiving the uncoded packets, even if they do not receive enough independent packets to decode the block. We find that this feature is specially suitable for SUs, since their transmissions may be interrupted at any time. However, the proportion of uncoded packets as well as that of coded packets must be allocated reasonably. Specifically, according to the estimated idle duration I, the SUs should predefine the number of time slots for transmitting uncoded packets (also can be seen as the block size), e.g., k, and the number of time slots for transmitting coded packets, e.g., $I-k$.

There is a tradeoff between the value of k and achieved throughput gain. Suppose the real idle duration is R. The current available time for SUs is actually $\min\{I, R\}$ time slots but we can only observe I before transmitting, so the value of k can only be determined based on I other than R. If k is too small, all k data packets may be decoded with high probability even if R is no more than I, but the throughput is also small.[2] On the contrary, with too large k, although the possible throughput gain may be high, the decoding probability of the block is low once I is bigger than R, and the throughput also degrades. To sum, the value of k should be carefully selected to maximize the expectation of successfully delivered packets while considering the possible relationship between I and R.

4. Handling the uncertainty of the idle duration

We propose two idle duration selection schemes for SUs, i.e., CIE-based algorithm and MAB-based algorithm respectively. The first scheme suits for the case when the idle duration follows some known distribution but its parameter is unknown. And the second scheme works for a general case when the idle duration is non-stochastic.

4.1. CIE-based algorithm for stochastic idle durations

In this scheme, the SUs first collect the statistics of the idle duration by sensing the channel for some rounds, and then estimate the parameters of the distribution by confidence interval estimation (CIE) [42]. Suppose the channel idle duration i follows some probability distribution, i.e., $I\sim\Theta(\xi_1,\xi_2,\ldots,\xi_f)$, where $\xi_1,\xi_2,\ldots,\xi_f$ are the parameters. Since most existing works are based on the geometric assumption [17,39], etc, we also assume that $I\sim G(p)$[3] and the corresponding probability distribution is given as follows

$$P\{I=i\}=p(1-p)^{i-1}, i=1,2,\ldots, \tag{1}$$

where p is the unknown geometric distribution parameter. The SUs first listen the channel and collect several idle durations as the sample, e.g., $I_1,I_2,\ldots,I_l$. We can easily obtain that the point estimator of p is $\hat{p}=\frac{1}{\bar{I}}$, where $\bar{I}$ is the mean value of $I_1,I_2,\ldots,I_l$. When the sample size l is large enough, according to the central limit theorem, we approximately have $\frac{\bar{I}-E\bar{I}}{\sqrt{D\bar{I}}}\sim N(0,1)$, where $E\bar{I}$ and $D\bar{I}$ are the expectation and variance of $\bar{I}$ respectively, i.e., $E\bar{I}=\frac{1}{p}$ and $D\bar{I}=\frac{1-p}{lp^2}$. That is also, approximately, $\sqrt{l}\,\frac{p\bar{I}-1}{\sqrt{1-p}}\sim N(0,1)$.

For better readability, we describe the CIE method in detail as follows. Assume that the confidential level is $1-\alpha$. Then the interval estimate of p can be given by

$$P\{\hat{p}_1\le p\le\hat{p}_2\}\ge 1-\alpha, \tag{2}$$

where $\hat{p}_1$ and $\hat{p}_2$ are the roots of equation $\sqrt{l}\,\frac{p\bar{I}-1}{\sqrt{1-p}}=-Z_{\frac{\alpha}{2}}$ and equation $\sqrt{l}\,\frac{p\bar{I}-1}{\sqrt{1-p}}=Z_{\frac{\alpha}{2}}$, respectively. $Z_{\frac{\alpha}{2}}$ is the upper $\frac{\alpha}{2}$ percentile of $N(0,\ 1)$. By some operations, we have that the confidential interval estimate of p with confidential level $1-\alpha$ is $[\frac{2l\bar{I}-Z^2_{\frac{\alpha}{2}}-\Delta Z^2_{\frac{\alpha}{2}}}{2l\bar{I}^2},\frac{2l\bar{I}-Z^2_{\frac{\alpha}{2}}+\Delta Z^2_{\frac{\alpha}{2}}}{2l\bar{I}^2}]$, where Δ equals to $\sqrt{Z^4_{\frac{\alpha}{2}}-4l\bar{I}Z^2_{\frac{\alpha}{2}}+4l\bar{I}^2}$.

Since $EI=\frac{1}{p}$, we then have

$$\frac{2l\bar{I}^2}{2l\bar{I}-Z^2_{\frac{\alpha}{2}}+\Delta Z^2_{\frac{\alpha}{2}}}\le EI\le\frac{2l\bar{I}^2}{2l\bar{I}-Z^2_{\frac{\alpha}{2}}-\Delta Z^2_{\frac{\alpha}{2}}}, \tag{3}$$

with probability $1-\alpha$. Based on the above observations, we develop the CIE-based algorithm for choosing stochastic idle durations, which is presented in Algorithm 1.

Algorithm 1 CIE-based algorithm for stochastic idle durations.

Parameters: real number $\alpha>0$ and l.
1: Sense the status of the channel until collecting a sequence of l idle durations, i.e., $I_1,I_2,\ldots,I_l$.
2: Calculate the mean of $I_1,I_2,\ldots,I_l$, i.e., $\bar{I}$, and the upper $\frac{\alpha}{2}$ percentile of $N(0,1)$, i.e., $Z_{\frac{\alpha}{2}}$.
3: Obtain the confidential interval of the idle duration according to Eq. (3), e.g., $EI\in[\hat{I}_1,\hat{I}_2]$.
4: Select the idle duration i uniformly from $[\hat{I}_1,\hat{I}_2]$ whenever the channel is sensed idle.

As shown in Algorithm 1, we first collect l idle durations by continuously sensing the channel in Step 1. Then, by Steps 2 and 3, we obtain the confidential interval of the idle duration, i.e., $EI\in[\hat{I}_1,\hat{I}_2]$. Lastly, for better flexibility, whenever the channel is idle, the current idle duration i is uniformly selected from $[\hat{I}_1,\hat{I}_2]$.

4.2. MAB-based algorithm for non-stochastic idle durations

When idle durations do not have stochastic characteristics, the expected idle duration is unpredictable. Here we propose a method of choosing idle duration based on MAB that can achieve almost optimal throughput. To be specific, we adopt MAB to develop the best strategy to select the idle duration in the long run. The key idea is as follows. At the beginning, we guess an optimal strategy. In the following rounds, we execute the strategy we guessed previously with some specific probability; otherwise, we try some other strategies in the strategy set. Our guess can be adjusted dynamically based on the feedback, i.e., the number of successfully delivered data packets. In both cases, we consider SNC in SUs' transmissions to achieve higher throughput, which will be discussed in detail in Section 5. Note that although the efficiency of the MAB algorithm is directly related to the exact SNC scheme, its optimality is not hurt as long as the transmission scheme stays unchanged. In other words, the idle duration selection is relatively independent from the SUs' data transmission policy.

4.2.1. Overview

For completeness, we present the MAB-based scheme as shown in Algorithm 2. Like previous studies based on MAB [21], we also employ a parameter γ to tradeoff between the *exploitation* and *exploration* in the problem of choosing the idle duration. γ is a relatively small parameter whose value depends on the number of

[2] Note that as stated in [10], the throughput gain by network coding usually increases with the large block size, and vise versa.

[3] For other distributions, this method can also be modified to estimate the confidential interval of their expectations in the same way.

Algorithm 2 MAB-based algorithm for non-stochastic idle durations.

Parameters: real number $\beta > 0$ and $0 < \eta, \gamma < 1/2$.
Initialization: Set the initial strategy weights for all the idle durations: $w_i(0) = 1$, for $i = 1, 2, \ldots, I_{\max}$.
For round $t = 1, 2, \ldots, T$
1: Calculate the strategy probability distribution:
$p_i(t) = (1-\gamma)\frac{w_i(t-1)}{\sum_{i=1}^{I_{\max}} w_i(t-1)} + \frac{\gamma}{I_{\max}}$, for $i = 1, 2, \ldots, I_{\max}$.
2: Choose the strategy i_t in tth round according to the above probability distribution, and transmit data by SNC.
3: Get the scaled output $g_{i_t}(t) \in [0,1]$ after the round based on the feedback from all SU receivers.
4: For $j = 1, 2, \ldots, I_{\max}$, set

$$g'_j(t) = \begin{cases} \frac{g_j(t)}{p_j(t)} + \frac{\beta}{p_j(t)} & \text{if } j = i_t \\ \frac{\beta}{p_j(t)} & \text{otherwise} \end{cases}$$

5: Update all the weights as
$w_j(t+1) = w_j(t)\exp(\eta g'_j(t))$, for $j = 1, 2, \ldots, I_{\max}$.

rounds T. Initially, we choose a random idle duration from Φ by setting equal weighs for all idle durations, as we do not know the relationship between the gain and idle duration at all in the beginning.

In the following rounds, we will *exploit* the strategy used in previous round with probability $1-\gamma$. The exploitation can guarantee an almost optimal performance if the previously strategy is also almost optimal. On the other hand, with probability γ, we will *explore* new idle durations, selecting each idle duration with equal probability $\frac{1}{I_{\max}}$. The exploration is also important in the sense that it can improve our strategy to the optimal solution eventually. The calculation of $p_i(t)$ in step 1 represents the tradeoff between the exploitation and exploration. In steps 2 and 3, the transmission is executed according to the selected i_t and corresponding SNC, and get the output afterwards. In steps 4 and 5, we calculate the gain of the current strategy, and update all the weights, respectively.

Note that the parameter β is to control the bias in estimating the idle duration gain $g'_i(t)$ and η is used to control the learning speed. The values of β, η and γ are very critical to the performance of the MAB algorithm, which will be discussed in the following part.

4.2.2. Theoretic analysis

In this part, we analyze the performance of the MAB algorithm theoretically. Firstly, we show that the regret of the algorithm is $O(\sqrt{TI_{\max}\ln I_{\max}})$, where T is the number of total rounds and $I_{\max}$ is the size of the strategy space Φ. Based on the regret analysis, we then prove that our algorithm is almost throughput-optimal.

Theorem 1. *For any* $\delta \in (0, 1)$, *when* $\beta = \sqrt{\frac{1}{TI_{\max}}\ln\frac{I_{\max}}{\delta}}$, $\eta = \sqrt{\frac{\ln I_{\max}}{4TI_{\max}}}$, *and* $\gamma = \sqrt{\frac{I_{\max}\ln I_{\max}}{T}}$, *with probability 1 - δ, the regret of Algorithm 2 is bounded by* $\tau \le 6\sqrt{TI_{\max}\ln I_{\max}}$.

Proof. The proof follows from the similar techniques in [21], which is omitted here due to space limitation and provided in the supplementary documents. □

According to Section 3.2, the throughput difference between our algorithm and the static optimal strategy can be as $\frac{\tau}{T'}$, where T' is the system life time. Therefore, based on Theorem 1, we can prove that the throughput of our algorithm is close to that of the optimal fixed algorithm in the long run.

Theorem 2. *Algorithm 2 is almost throughput-optimal when the number of rounds T is sufficiently large.*

Proof. According to Theorem 1, we have $\frac{\tau}{T'} \le \frac{\tau}{\sum_{t=1}^{T} m_t t_s + \sum_{t=1}^{T}\alpha_t i_t} \le \frac{6\sqrt{TI_{\max}\ln I_{\max}}}{Tt_s + \sum_{t=1}^{T} i_t} \le \frac{6\sqrt{TI_{\max}\ln I_{\max}}}{Tt_s + T} = \frac{1}{\sqrt{T}} \cdot \frac{6\sqrt{I_{\max}\ln I_{\max}}}{t_s+1}$. Therefore, when T is sufficiently large, the throughput of our algorithm is almost optimal. □

5. Utilizing systematic network coding for SUs' data transmission

In this section, we focus on utilizing SNC for SUs' transmission to improve the throughput performance, provided that an idle duration I is determined. In I time slots, k uncoded packets and $I-k$ coded packets are to be sent. The key issue is to determine a value k^*, which maximizes the expected number of delivered packets within I time slots. Worth emphasizing that since the exact duration R may be not equal to I, we exploit an opportunistic policy as follows. First of all, the data packets are transmitted according to the predetermined k^* in the beginning. As the transmission is in progress, if SUs find that I is smaller than R, implying that the channel is still idle, the SUs can transmit packets by the plain transmission scheme after the current block is decoded. Contrarily, if I is bigger than R, the SU receivers can still obtain some original packets due to the characteristic of SNC if the block is not decoded. All in all, SUs utilize opportunistic SNC (OSNC) to transmit as many data packets as possible.

5.1. Correlation among receivers' receptions under SNC

In this part, we will explicitly introduce the complicated correlation among receivers' receptions under SNC by using a toy example. Let $\mathbb{N}$ denote the set of receivers $\{1, 2, \ldots, N\}$, and $\mu_{\mathbb{N}}$ represent the number of delivered packets to all receivers within I time slots. S_n is the set of decoded packets at receiver n within I time slots. According to our definition of throughput, $\mu_{\mathbb{N}}$ is equal to the size of the intersection of S_n, i.e., $\mu_{\mathbb{N}} = \| \bigcap_{n\in\mathbb{N}} S_n \|$. Under RLNC, we easily have $\| \bigcap_{n\in\mathbb{N}} S_n \| = \min_{n\in\mathbb{N}} \| S_n \|$ [33]. However, in our problem $\| \bigcap_{n\in\mathbb{N}} S_n \|$ is not always equal to $\min_{n\in\mathbb{N}} \| S_n \|$. This is due to the correlation between receptions at different receivers under SNC. And this correlation brings challenges to search the optimal block size for SNC. We illustrate the problem by a simple example as shown in Table 2.

Suppose that there are three receivers and six time slots available as illustrated in Table 2. The sender employs the block size as three and broadcasts six packets using SNC in the six time slots. Due to the independent and heterogeneous channel loss, receiver 1 receives $X_1, X_1+X_2+X_3, X_1+2X_2+X_3$, receiver 2 receives $X_2, 2X_1+X_2+3X_3$, and receiver 3 receives X_2, X_3. Therefore, $S_1 = \{X_1, X_2, X_3\}$, $S_2 = \{X_1, X_2\}$, and $S_3 = \{X_2, X_3\}$, which results in $\min_{n\in\mathbb{N}} \| S_n \| = 2$ but $\| \bigcap_{n\in\mathbb{N}} S_n \| = 1$. Accordingly, the reception correlation between receiver 2 and receiver 3 must be studied. The correlation is more complicated when the receiver set is bigger. This complicated correlation makes it hard to obtain the probability distribution of $\mu_{\mathbb{N}}$.

5.2. Block size selection for SNC

We will first derive the probability distribution of $\mu_{\mathbb{N}}$ by studying the relationship among receivers' reception with different set sizes, and then propose a polynomial complexity block size selection algorithm for SNC in this part. For convenience, we first define a function Q as $Q(u, v, \varepsilon) \triangleq \binom{u}{v}(1-\varepsilon)^v\varepsilon^{u-v}$, which denotes

Table 2
The correlation among receivers' receptions under SNC.

	X_1	X_2	X_3	$X_1+X_2+X_3$	$2X_1+X_2+3X_3$	$X_1+2X_2+3X_3$	S_n
Receiver 1	√	×	×	√	×	√	X_1, X_2, X_3
Receiver 2	√	√	×	×	×	×	X_1, X_2
Receiver 3	×	√	√	×	×	×	X_2, X_3

the probability when v events out of u i.i.d events with success probability $1-\varepsilon$ happen.

We start with the simple case when there is one receiver only, e.g., $\mathbb{N}=\{n\}$. In the one receiver case, without no correlation, we can easily draw the probability distribution of $\mu_{\{n\}}$ as follows

$\Pr\{\mu_{\{n\}}=z\} =$

$$\begin{cases} \sum_{k'=k}^{I} Q(I,k',1-\varepsilon_n) & z=k \\ Q(k,z,1-\varepsilon_n)\sum_{k'=0}^{k-z-1} Q(I-k,k',1-\varepsilon_n) & 0<z<k \\ 1-\sum_{k'=k}^{I} Q(I,k',1-\varepsilon_n) & \\ -Q(k,z,1-\varepsilon_n)\sum_{k'=0}^{k-z-1} Q(I-k,k',1-\varepsilon_n) & z=0. \end{cases} \tag{4}$$

When the receiver receives no less than k packets (coded or uncoded), it can decode the block, which corresponds to the first case in Eq. (4). When the receiver receives less than k packets (coded or uncoded), it can still decode several data packets by successfully receiving uncoded packets in the first k time slots. The second case in Eq. (4) captures this situation. Compared to RLNC, even if the SUs cannot accumulate enough coded packets before the return of PUs, they may partially recover data packets by SNC. The last case in Eq. (4) means that the receiver does not receive enough coded packets to decode the block or any uncoded packet.

Next we consider the general case when there are multiple receivers. We must study the reception correlation at different receivers. Similarly as in Eq. (4), we also derive the probability distribution of $\mu_{\mathbb{N}}$ in light of different possible values.

If $\mu_{\mathbb{N}}=k$, all the receivers can decode the block, implying that all receivers receive no less than k packets. Hence, the probability of $\mu_{\mathbb{N}}=k$ can be given by

$$\Pr\{\mu_{\mathbb{N}}=k\} = \prod_{n\in\mathbb{N}} \Pr\{\mu_{\{n\}}=k\} = \prod_{n\in\mathbb{N}}\sum_{k'=k}^{I} Q(I,k',1-\varepsilon_n). \tag{5}$$

If $\mu_{\mathbb{N}}=z$ ($0<z<k$), we need to study the exact reception at all receivers and the correlation among them. We derive the result by the recursion approach. Based on the total probability formula, we have that

$$\begin{aligned}\Pr\{\mu_{\mathbb{N}}=z\} &= \sum_{v=z}^{k}\Pr\{\mu_{\mathbb{N}}=z|\mu_{\{N\}}=v\}\Pr\{\mu_{\{N\}}=v\} \\ &= \sum_{u=z}^{k}\sum_{v=z}^{k}\Pr\{\mu_{\mathbb{N}}=z|\mu_{\mathbb{N}-\{N\}} \\ &= u,\mu_{\{N\}}=v\}\Pr\{\mu_{\{N\}}=v\}\Pr\{\mu_{\mathbb{N}-\{N\}}=u\}.\end{aligned} \tag{6}$$

From Eq. (6), we notice that $\Pr\{\mu_{\mathbb{N}}=z\}$ directly relies on $\Pr\{\mu_{\mathbb{N}-\{N\}}=u\}$. In other words, $\Pr\{\mu_{\mathbb{N}}=z\}$ can be recursively computed if $\Pr\{\mu_{\mathbb{N}}=z|\mu_{\mathbb{N}-\{N\}}=u,\mu_{\{N\}}=v\}$ and $\Pr\{\mu_{\{N\}}=v\}$ can be obtained. Note that $\Pr\{\mu_{\{N\}}=v\}$ can be easily calculated by Eq. (5). Furthermore, $\Pr\{\mu_{\mathbb{N}}=z|\mu_{\mathbb{N}-\{N\}}=u,\mu_{\{N\}}=v\}$ corresponds to the event that the number of decoded packets in the receiver set $\mathbb{N}$ is z on the premise that the number of decoded packets in the receiver set $\mathbb{N}-\{N\}$ and $\{N\}$ are u and v, respectively. Accordingly, the probability of the event is

$$\Pr\{\mu_{\mathbb{N}}=z|\mu_{\mathbb{N}-\{N\}}=u,\mu_{\{N\}}=v\} = \frac{\binom{v}{z}\binom{k-v}{u-z}}{\binom{k}{u}}. \tag{7}$$

Then, Eq. (6) can be rewritten as follows

$$\Pr\{\mu_{\mathbb{N}}=z\} = \sum_{u=z}^{k}\sum_{v=z}^{k}\frac{\binom{v}{z}\binom{k-v}{u-z}}{\binom{k}{u}}Q'\Pr\{\mu_{\mathbb{N}-\{N\}}=u\}, \tag{8}$$

where $Q'=Q(k,v,1-\varepsilon_N)\sum_{k'=0}^{k-v-1}Q(I-k,k',1-\varepsilon_N)$.

Based on Eq. (8), we propose Algorithm 3 to compute the probability distribution of $\mu_{\mathbb{N}}$. As shown in Algorithm 3, we first compute the probability distribution of $\mu_{\{n\}}$ for single receiver according to Eq. (5). Then, we recursively compute the probability distribution of $\mu_{\{1,2,\ldots,N'\}}$ from $N'=2$ to $N'=N$. The computation complexity of Algorithm 3 is polynomial as given by the following theorem.

Algorithm 3 Recursive computation algorithm.

Input: Idle duration I, number of uncoded packets k, number of receivers N, and channel loss rates $\{\varepsilon_n\}_{n\in\mathbb{N}}$.
1: For $n=1, 2, \ldots, N$ and $z=1, 2, \ldots, k$, compute $\Pr\{\mu_{\{n\}}=z\}$ according to Eq. (3).
2: Set $N'=1$.
3: Substitute $N'+1$ for N', and update $\Pr\{\mu_{\{1,2,\ldots,N'\}}=z\}$ $=\sum_{u=z}^{k}\sum_{v=z}^{k}\frac{\binom{v}{z}\binom{k-v}{u-z}}{\binom{k}{u}}Q'\Pr\{\mu_{\{1,2,\ldots,N'-1\}}=u\}$, where $Q'=Q(k,v,1-\varepsilon_{N'})\sum_{k'=0}^{k-v-1}Q(I-k,k',1-\varepsilon_{N'})$.
4: If $N'==N$, stop; otherwise go to step 3.
Output: $\{\Pr\{\mu_{\mathbb{N}}=z\}\}_{z=1,2,\ldots,k}$.

Theorem 3. *Algorithm 3 is a polynomial-time algorithm and the complexity is upper bounded by $O(NI^3)$, where N is the number of receivers and I is the number of time slots estimated.*

Proof. We first analyze the computation complexity when $\mu_{\mathbb{N}}$ equals to k. From Eq. (5), to compute $\Pr\{\mu_{\mathbb{N}}=k\}$, we need to traverse over I time slots and N receivers respectively, so this complexity is $O(NI)$. For $\mu_{\mathbb{N}}<k$, the calculation of $\Pr\{\mu_{\mathbb{N}}=z\}$ depends on $\Pr\{\mu_{\mathbb{N}-\{N\}}=u\}$ $(z<=u<=I)$. If $\Pr\{\mu_{\mathbb{N}-\{N\}}=u\}$ $(z<=u<=I)$ has been obtained, the computation process of $\Pr\{\mu_{\mathbb{N}}=z\}$ needs to cycle over $[z, k]$ twice, and in each cycle it takes at most $k-z$ steps, which results in a complexity of $O(I^3)$. Besides, to compute $\Pr\{\mu_{\mathbb{N}}=k\}$ eventually, we also need to cycle over N receivers. So the complexity when $\mu_{\mathbb{N}}=k'$ $(k'<k)$ is $O(NI^3)$. To sum up, the computation complexity is $O(NI^3)$ and Theorem 3 follows. □

So far, under an idle duration I and the number of uncoded packets to be sent k, we are able to derive the probability distribution of $\mu_{\mathbb{N}}$ (number of delivered packets) in polynomial time according to Algorithm 3. Therefore, the expected reward (number of expected delivered packets) when choosing k can be given by

$$R_k = \sum_{z=1}^{k} z\Pr\{\mu_{\mathbb{N}}=z\},\ \text{ for } k=1,2,\ldots,I. \tag{9}$$

From Eq. (9) and Algorithm 3, we are able to compute the exact expected reward (throughput) for each $k=1,2,\ldots,I$. However, as shown in the equations, the general analytic expressions are hard to obtain, and we cannot see any monotonicity in the expression neither. As an example illustrating the complex relationship between the block size and the expected throughput gain, we

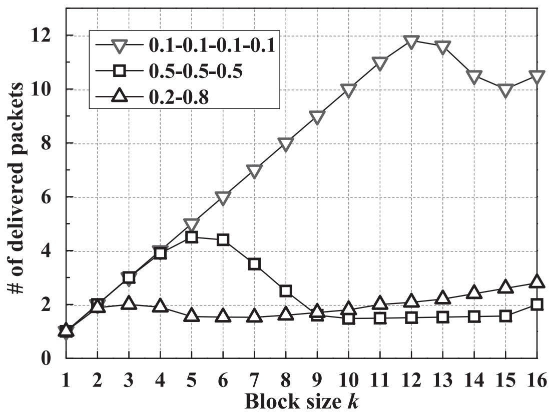


Fig. 3. Number of delivered packets with different block size k under SNC.

present the following numeric analytic results as shown in Fig. 3. The figure illustrates the relationship between the expectation of number of delivered packets and the value of k with the number of available time slots I fixed at 16. In the figure, the line labeled 0.1-0.1-0.1-0.1 represents that there are four SU receivers, and the channel erasure rate to each receiver is 0.1. Note that the number of delivered packets represents the achieved throughput, since I is fixed. The two other lines have the similar meanings. From the figure, generally, too small or too large value of k may not obtain the highest throughput. Also, for different number of receivers and different channel erasures, the throughput-block size curve varies. And the optimal value of block size, i.e., k^*, is not always in the middle of the interval $[1, I]$. This shows the tradeoff between the value of k and the achieved throughput gain. It also inspires us that the value of k should be carefully selected to maximize the throughput, by searching all possible values. Therefore, we propose the following exhaustive computation based block size selection algorithm of SNC as shown in Algorithm 4.

Algorithm 4 Block size selection algorithm of SNC.

Input: Idle duration I, number of receivers N, and channel loss rates $\{\varepsilon_n\}_{n\in\mathbb{N}}$.
Initialization: Set $k^* = 0$, $R^* = 0$.
For each $k = 1, 2, \ldots, I$
Compute $\Pr\{\mu_{\mathbb{N}} = z\}$ by Algorithm 3 for $z = 1, 2, \ldots, k$, then compute R_k by Eq. (9).
If $R_k > R^*$ **then**
$k^* \leftarrow k$, $R^* \leftarrow R_k$.
Output: k^*.

Algorithm 4 selects the block size k^* by traversing all possible values to maximize the expectation of number of delivered data packets in I time slots. Although Algorithm 4 employs an exhaustive search, the computation complexity is polynomial, which is provably shown in the following theorem.

Theorem 4. *Algorithm 4 is a polynomial-time algorithm and the complexity is upper bounded by $O(NI^4)$, where N is the number of receivers and I is the number of time slots estimated.*

Proof. According to Theorem 3 and Eq. (9), for a given k, the computation of R_k takes $O(NI^3)$. To obtain the optimal block size k^*, we need to traverse from 1 to I. Therefore, the complexity of Algorithm 4 is bounded by $O(NI^4)$ and the theorem is thus proved. □

Remarks: By using Algorithm 4, after determining an idle duration I, the SU sender can compute a block size k^* and then sends packets according to this predefined rule. In practical, the block may be decoded by all receivers before the return of the PU, in this case the SUs switch to non-network coding mode in the remaining time. Since our algorithms are polynomial-time complexity, Algorithm 4 can be implemented online, which is favorable for SUs to adaptively adjust the transmission scheme with small delay.

6. Discussion on multiple PU channels

Our proposed solution framework can be readily extended to the scenario where there are multiple PU channels. Assume that there are C orthogonal channels, where each channel is occupied by one PU and the activity of each PU is independent. The set of channels is denoted by $\mathcal{C} = \{1, 2, \ldots, C\}$. In a word, to combat the uncertainty of idle durations, our approach for the stochastic idle durations can be attributed to some kind of learning before transmitting. Comparatively, for non-stochastic idle durations, we follow the idea of learning while transmitting. Next, we will discuss how to extend our approach to multiple PU channels for the two cases respectively.

6.1. Stochastic idle durations

When the idle duration of any channel follows some probability distribution, we allow the SUs "listen" each channel one by one. Specifically, the SUs sense channel $c \in \mathcal{C}$ until the collected idle durations are enough to estimate the expectation value of idle durations of this channel, i.e., EI_c. In light of Algorithm 1, the SUs need CI idle durations in total to obtain the confidential interval of the idle duration for each channel. Suppose that the confidential level for each channel is identical, i.e., $1 - \alpha$. Thus, similar to Algorithm 1, the confidential interval of the idle duration for channel c can be obtained as $EI_c \in [\hat{I}_{c1}, \hat{I}_{c2}]$, for all $c \in \mathcal{C}$.

After estimating the confidential interval for all channels, the SUs turn into the data transmission process. Firstly, the SUs always access the channel with the largest mean of confidential interval from the current available channels after sensing. If the available channel set $\mathcal{C}_a$ is $\{c_1, c_2, \ldots, c_s\} \subseteq \mathcal{C}$, the channel c^* for SUs is selected as follows

$$c^* = \arg\max_{c\in\mathcal{C}_a}\{\tfrac{\hat{I}_{c1}+\hat{I}_{c2}}{2}\}. \quad (10)$$

Then, the SUs select an idle duration I uniformly from $[\hat{I}_{c^*1}, \hat{I}_{c^*2}]$, and determine the coding parameter k^* by Algorithm 4.

6.2. Non-stochastic idle durations

When the idle duration of any channel does not follow any probability distribution, we employ a two-dimensional MAB approach. Similar with the one-dimensional MAB for the one single PU channel case, a SU sender's action is defined by a choosing/sensing/transmitting strategy $\psi_t = < c_t, \alpha_t, i_t >$. For each round t, $c_t \in \mathcal{C}$ is the chosen channel, α_t still denotes whether the SUs access the channel or not, and $i_t \in \{1, 2, \ldots, I_{\max}\}$ is the idle duration selected. α_t is a 0–1 variable, whose value is determined according to the sensing result: $\alpha_t = 1$ if the channel is busy and $\alpha_t = 0$ otherwise. At each round t, the SU sender should choose a strategy vector $< c_t, i_t >$ over strategy space $\varphi \triangleq \{1, 2, \ldots, C\} \times \{1, 2, \ldots, I_{\max}\}$. The gain of each strategy and corresponding regret can be defined similar as in the one-dimensional MAB scheme, except that the strategy is replaced by ψ_t. The modified two-dimensional MAB algorithm is shown in Algorithm 5.

6.2.1. Algorithm overview

Similar as in Algorithm 2, the SUs choose the channel-idle duration vector $< c_t, i_t >$ over φ according to the corresponding probability distribution $\{p_{c,\,i}\}_{(c,\,i)\,\in\,\varphi}$. At the first round, the strategy

Algorithm 5 Modified two-dimensional MAB algorithm for SUs with SNC under multiple PU channels.

Parameters: Real number $\beta' > 0$ and $0 < \eta', \gamma' < 1/2$.
Initialization: Set the initial strategy weights for all the channel-idle duration pairs: for $c = 1, 2, \ldots, C$, and $i = 1, 2, \ldots, I_{\max}$, $w_{c,i}(0) = 1$.
For round $t = 1, 2, \ldots, T$
1: Calculate the strategy probability distribution:
$p_{c,i}(t) = (1-\gamma')\frac{w_{c,i}(t-1)}{\sum_{c=1}^{C}\sum_{i=1}^{I_{\max}} w_{c,i}(t-1)} + \frac{\gamma'}{CI_{\max}}$, for $c = 1, 2, \ldots, C$, and $i = 1, 2, \ldots, I_{\max}$.
2: Choose the strategy (c_t, i_t) in tth round according to the probability distribution, transmit data by SNC to the SU receivers under channel c_t, based on the idle duration i_t and corresponding block size k_t by Algorithm 4.
3: Get the scaled output $g_{c_t,i_t}(t) \in [0, 1]$ after the round based on the feedback from all SU receivers.
4: For $c = 1, 2, \ldots, C$, and $i = 1, 2, \ldots, I_{\max}$, set

$$g'_{c,i}(t) = \begin{cases} \frac{g_{c,i}(t)}{p_{c,i}(t)} + \frac{\beta'}{p_{c,i}(t)} & \text{if } c = c_t \text{ and } i = i_t \\ \frac{\beta'}{p_{c,i}(t)} & \text{otherwise} \end{cases}$$

5: Update all the weights as
$w_{c,i}(t) = w_{c,i}(t-1)\exp(\eta' g'_{c,i}(t))$, for $c = 1, 2, \ldots, C$, and $i = 1, 2, \ldots, I_{\max}$.

probability is uniformly distributed, i.e., $p_{c,i}(1) = \frac{1}{CI_{\max}}$ $(\forall (c, i) \in \varphi)$, in the sense that the SUs begin to explore the best strategy pair uniformly over the entire strategy space φ. From the second round, $p_{c,\,i}$ is determined by the corresponding strategy weight $w_{c,\,i}$ in the overall strategy weights. The parameter γ' is used to tradeoff between exploration and exploitation. With probability $1-\gamma'$, we will exploit the best channel-idle duration pair in previous rounds, while with probability γ' exploring new channel-idle duration pair equally.

6.2.2. Theoretic analysis

With similar analysis, we can analyze the performance of the modified two-dimensional MAB algorithm in terms of regret, and have the two following propositions.

Proposition 1. *For any $\delta' \in (0, 1)$, when $\beta' = \sqrt{\frac{1}{LT}\ln\frac{L}{\delta'}}$, $\eta' = \sqrt{\frac{\ln L}{4TL}}$, and $\gamma' = \sqrt{\frac{L\ln L}{T}}$, with probability 1-$\delta'$, the regret of Algorithm 5 is bounded by $\tau' \le \sqrt{TL\ln L}$, where $L = CI_{\max}$.*

Proof. The detailed proof is provided in the supplementary documents. □

Proposition 2. *Algorithm 5 is almost throughput-optimal when T is sufficiently large.*

Proof. The proof is similar as in Theorem 2, which is omitted here. □

7. Performance evaluation

In this section, via simulations, we evaluate the performance of OSNC with the CIE-based algorithm under stochastic idle durations, and that with the MAB-based algorithm under non-stochastic idle durations, respectively. We take the scheme with perfect idle duration information using OSNC as a reference, whose performance is the upper bound of our schemes. For comparison, we also include plain retransmission scheme and the adaptive RLNC scheme proposed in [33], which are refereed to “Plain Retransmission” and “ORLNC” respectively in the simulation study. Note that [33] proposes an optimal adaptive network coding scheme to adjust the block size according to the remaining time to the hard deadline. We first present the results of the four schemes under the stochastic idle durations case, and then the results under the non-stochastic idle durations case. Besides, we also define a new metric named “utilization”, which is the ratio of the performance of OSNC/ORLNC/Plain Retransmission to the upper bound. This metric can precisely characterize the efficiency of SUs utilizing the spectrum holes in CRNs. Moreover, we present the practical regrets of our MAB-based algorithm to validate the regret bound analysis. Lastly, we evaluate the performance of OSNC* compared with OSNC, to explore the tradeoff between throughput and delay in SUs’s network coding-based data transmissions. Note that the only difference between OSNC* and OSNC is that in OSNC* the block not completed in one idle duration will continue in the next idle duration.

7.1. Evaluation results

7.1.1. Simulation setting

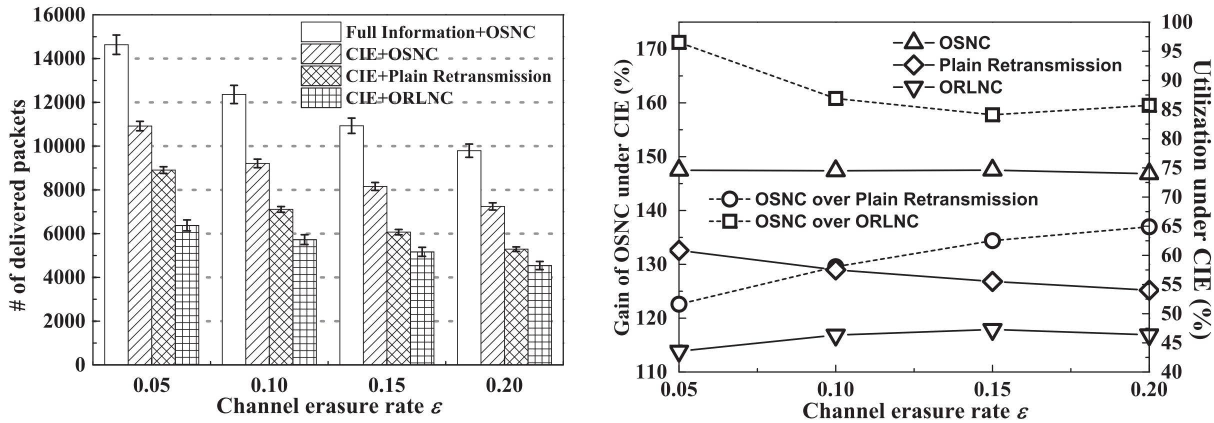
For the stochastic idle durations, as stated in Section 4.1, we take geometric distribution as an example and utilize CIE method to estimate the expectation of the idle durations. In the simulation, we find that setting the confidence level $1-\alpha$ as 95% and sample size l as 100 is precise enough. Thus, the simulation results are based on the aforementioned parameters.

For the non-stochastic idle durations, we mix several different probability distributions to simulate a trace of non-stochastic idle durations. In this study, due to space limitation, we only present two representative cases. One consists of an uniform distribution $U[A, B]$, a geometric distribution $G(p)$ and a poisson distribution $P(\lambda)$. Another is composed of a normal distribution $N(\mu, \sigma^2)$, a binomial distribution $B(K, q)$ and a hypergeometric distribution $H(n, M, N)$. Specifically, we generate three sequences of the distributions and then everyone of the trace data is chosen from these distributions with equal probability. In this way, the generated sequence does not follow any probability distribution. We set the distribution parameters $A = 30$, $B = 50$, $p = 0.025$, $\lambda = 50$, $\mu = 25$, $\sigma = 10$, $K = 40$, $n = 60$, $M = 30$ and $N = 40$ as an illustration in this paper. The number of total rounds T is fixed at 1000.

7.1.2. Stochastic idle durations

This part presents the performance of OSNC compared with Plain Retransmission and ORLNC under stochastic idle durations, when the channel erasure rate and idle duration distribution parameter vary respectively.

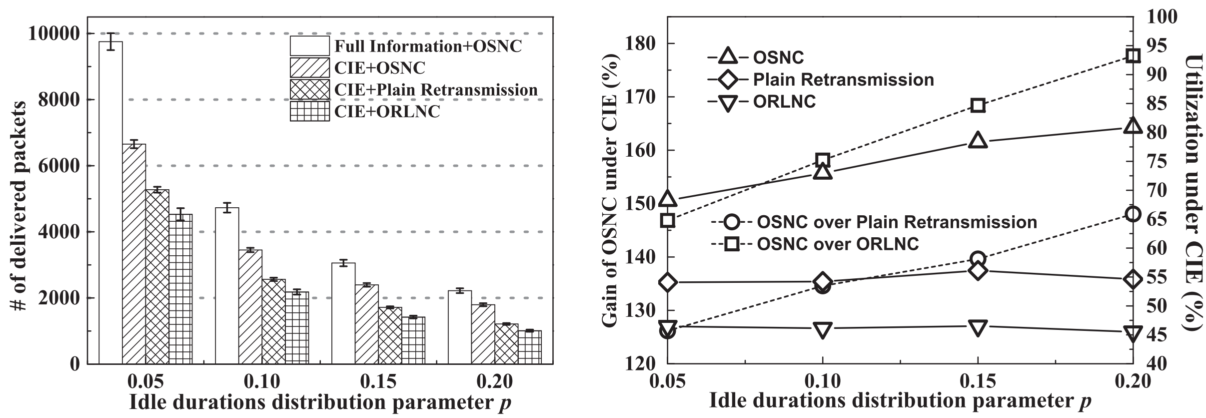
Firstly, Fig. 4 describes the performance of different transmission schemes under different channel erasure rates. From Fig. 4(a), we know that the proposed OSNC can always achieve the highest performance among the three schemes (OSNC, ORLNC, Plain Retransmission), no matter how the channel quality deteriorates. This realizes the promising performance gains of network coding in the transmission of SUs. However, we also notice that ORLNC performs worse than Plain Retransmission all the time. This is because with ORLNC, the SU sender chooses one relatively large block size to expect high throughput and every SU receiver must collect enough coded packets to decode the block. Nevertheless, the predicted idle duration may be larger than the exact idle duration with high probability. Once this happens, those coded packets received by SU receivers are useless and the throughput is thus extremely low. Comparatively, with OSNC, the sender will send some



(a) Performance of different schemes under different channel qualities.

(b) Gain of OSNC and utilization of different schemes under stochastic idle durations.

Fig. 4. Performance under *stochastic* idle durations when channel quality ϵ varies.



(a) Performance of different schemes under different distribution parameters.

(b) Gain of OSNC and utilization of different schemes under stochastic idle durations.

Fig. 5. Performance under *stochastic* idle durations when distribution parameter p varies.

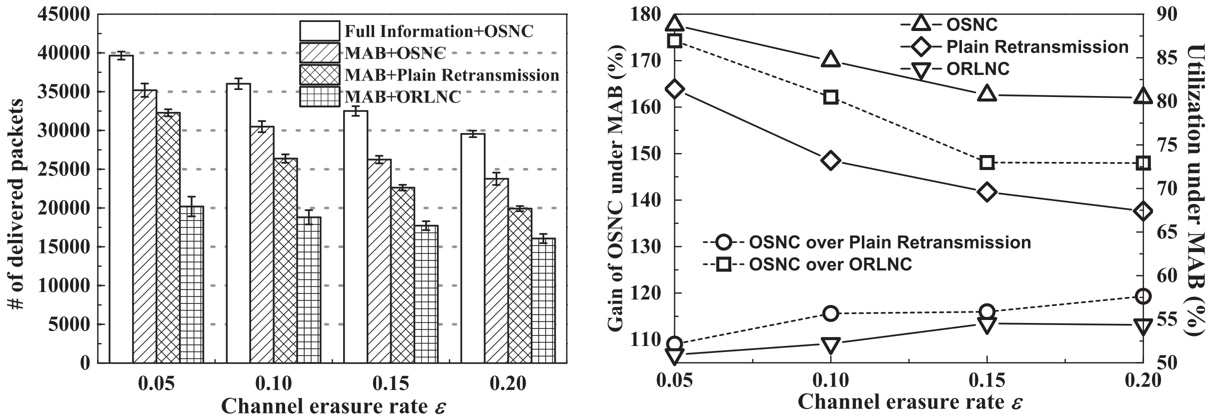
uncoded packets first, which enables the SU receivers can still obtain some data packets even when they cannot decode. This shows the advantage of OSNC when facing the uncertainty of available time in the transmission of SUs.

Furthermore, as shown in Fig. 4(b), the gain of OSNC over Plain Retransmission increases from 120% to 136% with the channel quality deterioration. This is because when the channel deteriorates, the SUs need less redundant transmissions with OSNC than that with Plain Retransmission as the later coded packets are useful for all SU receivers. On the contrary, the gain of OSNC over ORLNC decreases from 185% to around 158% when the channel erasure rate varies from 0.05 to 0.20. This is due to the reason that both OSNC and ORLNC will select small block sizes when the channel quality becomes worse. Also, from Fig. 4(b), we find that, with CIE, OSNC achieves better utilization than Plain Retransmission and ORLNC, with a steady value around 75%.

Lastly, Fig. 5 plots the performance of the four schemes when the distribution parameter p changes. Note that the expectation of a geometric distribution is inversely proportional to its parameter, so the expected idle duration becomes smaller as p increases. This leads to the decrease of the number of delivered packets by all the four schemes when p increases as shown in Fig. 5(a). However, OSNC achieves higher performance than Plain Retransmission and ORLNC due to its high utilization of the available time. And in Fig. 5(b), the gain of OSNC over both Plain Retransmission and ORLNC keeps growing with the increase of p, from 125% to 148% and 147% to 177% respectively. This shows the advantage of our proposed OSNC even when the available time is scarce. Additionally, the utilization of OSNC also increases with the increase of p up to about 80%, while both Plain Retransmission and ORLNC achieve low utilization, 55% and 45%, respectively.

7.1.3. Non-stochastic idle durations

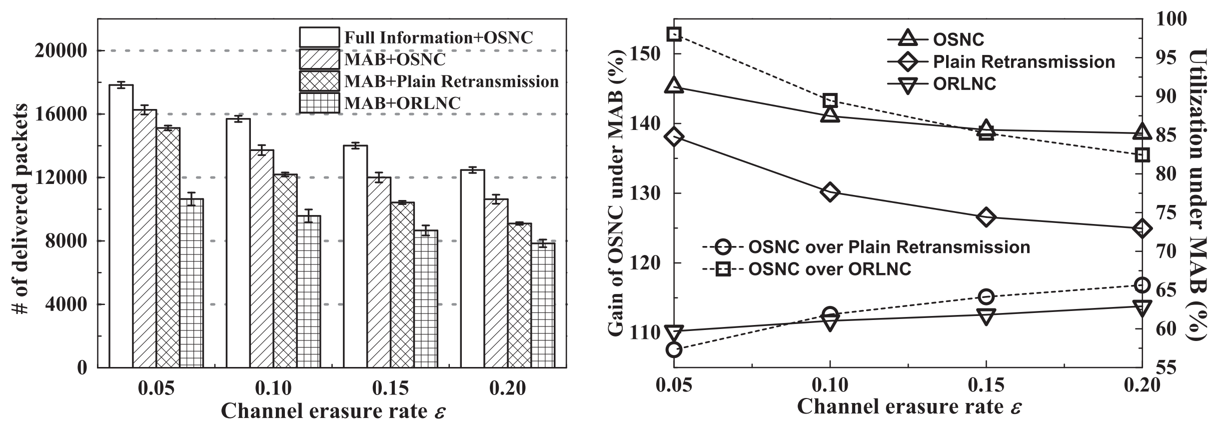
Fig. 6 illustrates the performance of the four schemes under non-stochastic idle durations for the first mixed distribution, with the variation of channel quality ε. Comparing Figs. 4 and 6, we find that OSNC achieves similar performance, showing that OSNC always performs better, its gain over Plain Retransmission increases as ε increases and that over ORLNC shows a contrary trend. We also notice that the gain of OSNC over Plain Retransmission in the non-stochastic case is not as high as that in the stochastic case, up to only about 19%. And the similar phenomenon can be found in the gain of OSNC over ORLNC. This phenomenon can be attributed to the reason that in the non-stochastic case, the exact idle duration is more difficult to estimate. This difficulty can influence the decision on the block size selection. In other words, once the estimated idle duration is longer than the exact idle duration, the throughput gain induced by OSNC will be smaller. However,



(a) Performance of different schemes under different channel qualities.

(b) Gain of OSNC and utilization of different schemes under non-stochastic idle durations.

Fig. 6. Performance under *non-stochastic* idle durations *I* when channel quality ε varies.



(a) Performance of different schemes under different channel qualities.

(b) Gain of OSNC and utilization of different schemes under MAB algorithm.

Fig. 7. Performance under *non-stochastic* idle durations *II* when channel quality ε varies.

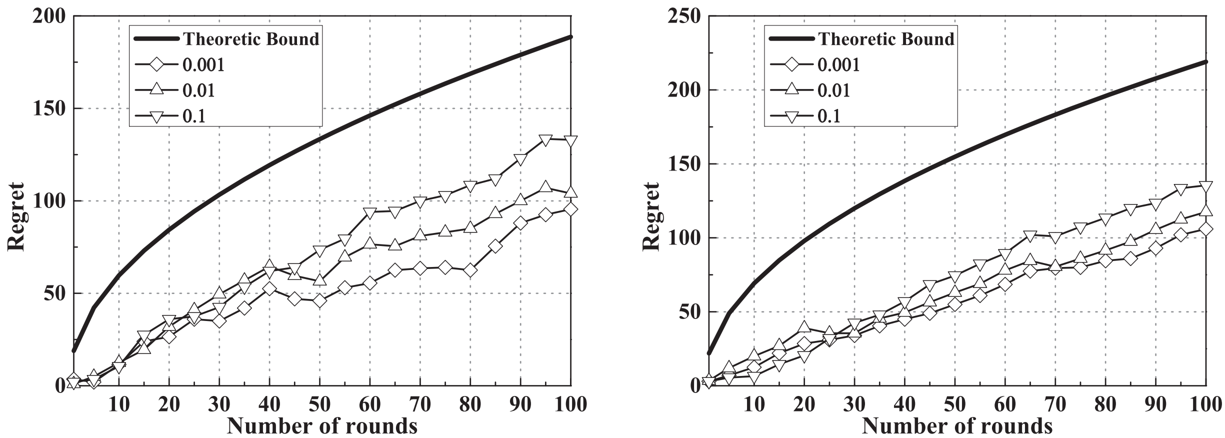
as illustrated in Fig. 6(b), our proposed scheme (OSNC with MAB) achieves relative good utilization under non-stochastic idle durations case, as high as nearly 90% when $\varepsilon = 0.05$. The similar trend can be found in Fig. 7 for the second mixed distribution.

7.2. Analysis of the practical regrets

To validate the regret bound analysis, we conduct simulations on the practical regrets achieved by the proposed MAB-based algorithm, compared with the corresponding theoretic bounds. Specifically, we fix the number of SU receivers N and the channel erasure rate ε_n at 10 and 0.1, respectively, and increase the number of rounds T from 1 to 100. To better investigate the regret, we let the parameter δ in Theorem 1 change from 0.001 to 0.1, which represents different confidential levels on the achieved regret bound. Fig. 8(a) and (b) show the practical regrets of Algorithm 2 compared with the theoretic bound derived by Theorem 1, under non-stochastic idle durations I and II, respectively. From the figures, we observe that the practical regrets of the proposed algorithm are upper bounded by the derived theoretic bound.

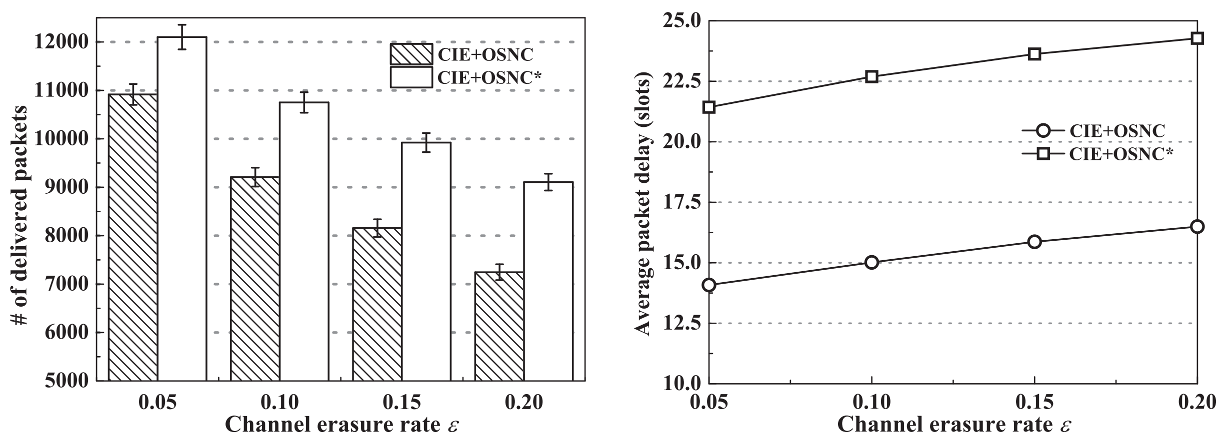
7.3. Tradeoff between throughput and delay

In this subsection, to explore the tradeoff between throughput and delay in network coding-based data transmissions in CRNs, we present the simulation results of OSNC* compared with OSNC, in terms of # of delivered data packets (represents throughput) and average packet delay. Specifically, as an example, we present the performance results of OSNC* and OSNC under the stochastic idle duration trace with the fixed p and non-stochastic idle duration trace I used in Section 7.1, when the channel erasure rate ϵ changes. Fig. 9(a) and (b) show # of delivered data packets and average packet delay of OSNC and OSNC* with CIE under stochastic idle durations, with the variation of channel erasure rate ϵ. From Fig. 9(a), we can obtain that OSNC* performs better than OSNC in terms of # of delivered data packets, since in OSNC* the block that is not decoded in one idle duration can continue in the next idle duration while in OSNC any block must be completed in one idle duration. Although our proposed idle duration estimation schemes and OSNC can reduce the negative effect of the inaccuracy of idle duration selection, the chosen idle duration may still be larger than the real idle duration. Once this happens, all data packets in the block may be not decoded, which largely reduces the number of total delivered data packets. On the other side, Fig. 9(b) illustrates the cost of the higher throughput of OSNC*. Since some decoded blocks experience multiple idle durations and the busy duration among these idle durations, and the busy duration determined by PU may be long, the decoding delay of the packets in these block is obviously larger, which results in the larger average packet de-



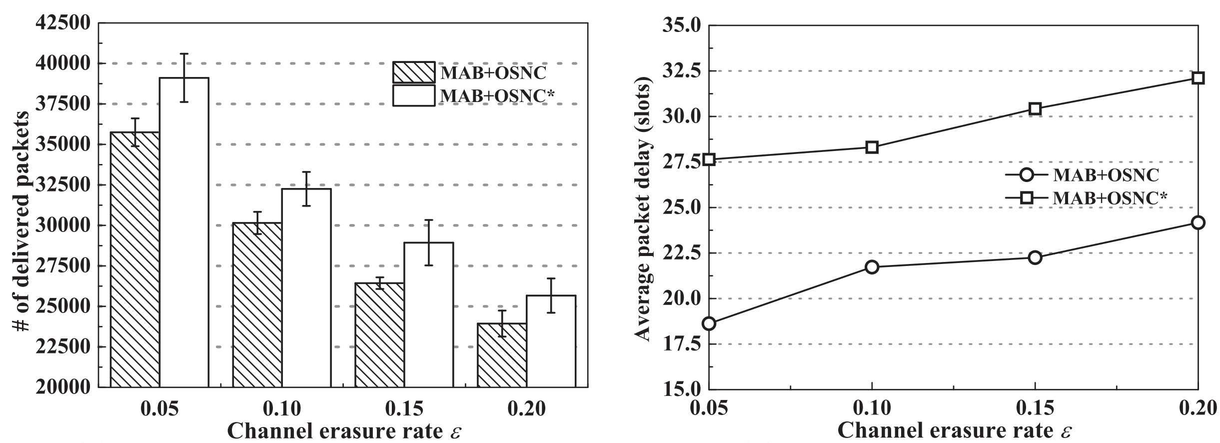
(a) Non-stochastic idle durations I. (b) Non-stochastic idle durations II.

Fig. 8. Practical regrets of Algorithm 2.



(a) # of delivered data packets. (b) Average packet delay.

Fig. 9. Performance comparison of OSNC and OSNC* under *stochastic* idle durations.



(a) # of delivered data packets. (b) Average packet delay.

Fig. 10. Performance comparison of OSNC and OSNC* under *non-stochastic* idle durations.

lay. Fig. 10(a) and (b) present the results of OSNC* and OSNC under non-stochastic idle durations, which also show the similar tradeoff between throughput and delay as in the stochastic case. This tells us if SUs' data flow is not delay-sensitive, we can use OSNC* instead of OSNC, to obtain higher throughput performance.

8. Discussion

Impact of sensing accuracy: Note that in previous analysis, we assume that the SUs can precisely sense the status of the channel. In real systems, we cannot precisely and timely sense the channel status. For example, there is a false alarm probability of channel sensing $P_f(t_s)$. Indeed, $P_f(t_s)$ will have negative effects on the

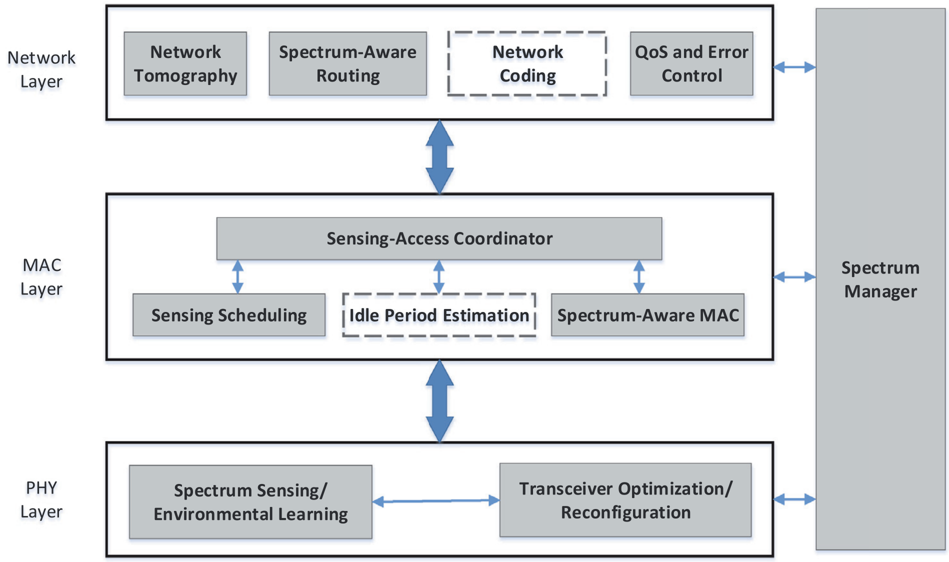


Fig. 11. Compatibility of the proposed framework to CRN standardization.

performance of OSNC because it would affect the selection of idle duration and furthermore make the block size selection inaccurately. However, $P_f(t_s)$ can be negligible if the sensing time t_s is long enough. Specifically, the false alarm probability can be approximated by $P_f(t_s) = Q((\frac{\epsilon_0}{\sigma_u^2} - 1)\sqrt{t_s B})$ [43], where $\frac{\epsilon_0}{\sigma_u^2}$ is the decision threshold for sensing, B is the channel bandwidth, $Q(\dot{})$ is the Q-function for the tail probability of the standard normal distribution, and t_s is the channel sensing time, if employing the energy detection for channel sensing. In practice, based on the above equation, we can choose an appropriate t_s to make $P_f(t_s)$ small enough, i.e., $P_f(t_s) \leq 0.01$. And we would like to incorporate this impact in future study.

Compatibility and applicability of the proposed framework: In the implementation, the proposed framework can be integrated in the MAC layer and Network layer in each node with moderate modification. Specifically, as shown in Fig. 11 [44], the network coding module can be added in the network layer similar as existing network coding protocols [8,9]. And the idle period estimation module including CIE- and MAB-based algorithms can be integrated under the sensing-access coordinator in the MAC layer. As to the applicability, our proposed framework is directly applicable to the scenario where a secondary user broadcasts messages to several other secondary users. The protocols should be added mainly including network coding protocol, which contains the encoding and decoding processes. Since our framework is centralized, SUs transmissions can be synchronized by using a fixed channel as the common control channel. The incurred overhead includes coding overhead, control information exchange overhead and spectrum sensing overhead, etc. All in all, our algorithms are well adapted to CRNs.

9. Conclusion and future work

In this paper, we for the first time build up an efficient network coding strategy for SUs, by considering the uncertain idle durations in CRNs. Our network coding schemes for SUs can be attributed to opportunistic systematic network coding (OSNC), which means that OSNC can opportunistically utilize the idle duration left by PUs. We propose a CIE-based algorithm to estimate the expectation of idle durations when the idle durations are stochastic, and a MAB-based algorithm to sequentially determine the idle duration for the non-stochastic case.

We then present a block size selection algorithm to select a block size to maximize the expected number of total decoded packets under a given idle duration. Besides, we discuss how to extend our algorithms when there are multiple PU channels. Our simulation study showed that, compared to the Plain Retransmission and general RLNC scheme, our proposed OSNC can always achieves the highest performance. Moreover, compared to the scheme with perfect idle duration information, our proposed schemes can achieve competitive performance. In the near future, we plan to extend the analysis to the multi-hop scenarios in CRNs, and study the performance of our strategy under more fruitful applications of SUs.

Supplementary material

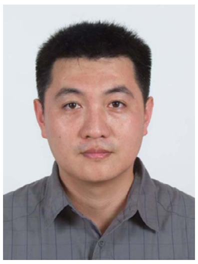
Supplementary material associated with this article can be found, in the online version, at 10.1016/j.adhoc.2016.12.009.

References

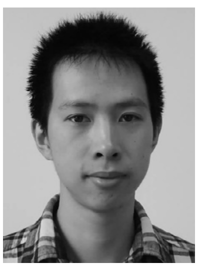
[1] J. Mitola, Cognitive radio: an integrated agent architecture for software defined radio, Ph.d. dissertation, KTH Royal Institute of Technology, 2000.
[2] I.F. Akyildiz, W.-Y. Lee, M.C. Vuran, S. Mohanty, Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey, Comput. Netw. 50 (13) (2006) 2127–2159.
[3] R. Ahlswede, N. Cai, S. Li, R. Yeung, Network information flow, IEEE Trans. Inf. Theory 46 (4) (2000) 1204–1216.
[4] A. Eryilmaz, A. Ozdaglar, M. Médard, On the delay and throughput gains of coding in unreliable networks, IEEE Trans. Inf. Theory 54 (12) (2008) 5511–5524.
[5] D. Lucani, M. Médard, M. Stojanovic, Random linear network coding for time–division duplexing: queueing analysis, IEEE Int. Symp. Inf. Theory (ISIT) (2009) 1423–1427.
[6] D. Nguyen, T. Tran, T. Nguyen, B. Bose, Wireless broadcast using network coding, IEEE Trans. Inf. Theory 58 (2) (2009) 914–925.
[7] B.T. Swapna, A. Eryilmaz, N.B. Shroff, Throughput-delay analysis of random linear network coding for wireless broadcasting, IEEE Int. Symp. Netw. Coding (NetCod) (2010) 1–6.
[8] S. Chachulski, M. Jennings, S. Katti, D. Katabi, Trading structure for randomness in wireless opportunistic routig, ACM SIGCOMM (2007) 169–180.
[9] P.A. Chou, Y. Wu, K. Jain, Practical network coding, Annu. Allerton Conf. Commun. Control Comput. (2003) 40–49.
[10] C. Fragouli, D. Lun, M. Médard, P. Pakzad, On feedback for network coding, in: 41st Annual Conference on Information Sciences and Systems (CISS), 2007, pp. 248–252.

[11] T. Shu, M. Krunz, Throughput-efficient sequential channel sensing and probing in cognitive radio networks under sensing erros, ACM MOBICOM (2009) 37–48.
[12] A. Anandlkumar, N. Michael, A.K. Tang, A. Swami, Distributed algorithm for learning and cognitive medium access with logarithmic regret, IEEE J. Sel. Areas Commun. (JSAC) 29 (4) (2011) 731–745.
[13] X.-Y. Li, P. Yang, Y. Yan, L. You, S. Tang, Q. Huang, Almost optimal accessing of nonstochastic channels in cognitive radio networks, IEEE Conf. Comput. Commun. (INFOCOM) (2012) 2291–2299.
[14] M. Maskery, V. Krishnamurthy, Q. Zhao, Decentralized dynamic spectrum access for cognitive radios: cooperative design of a noncooperative game, IEEE Trans. Commun. 57 (2) (2009) 459–469.
[15] Y. Xu, J. Wang, Q. Wu, Q. Anpalagan, Y.-D. Yao, Opportunistic spectrum access in unknown dynamic environment: a game-theoretic stochastic learning solution, IEEE Trans. Wireless Commun. (TWC) 11 (4) (2012) 1380–1391.
[16] A. Palaios, J. Riihijärvi, O. Holland, A. Achtzehn, P. Mähönen, Measurements of spectrum use in london: exploratory data analysis and study of temporal, spatial and frequency-domain dynamics, in: 2012 IEEE International Symposium on Dynamic Spectrum Access Networks (DYSPAN), 2012, pp. 154–165.
[17] M. Wellens, J. Riihijärvi, P. Mähönen, Evaluation of adaptive MAC-layer sensing in realistic spectrum occupancy secnarios, in: IEEE Symposium on New Frontiers in Dynamic Spectrum (DySPAN), 2010, pp. 1–12.
[18] C. Ghosh, S. Pagadarai, D.P. Agrawal, A.M. Wyglinski, A framework for statistical wireless spectrum occupancy modeling, IEEE Trans. Wireless Commun. (TWC) 9 (1) (2010) 38–44.
[19] S. Pagadarai, A.W. Wyglinski, A quantitative assessment of wrieless spectrum measurements for dynamic spectrum access, in: 2009 4th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM), 2009, pp. 1–5.
[20] J. Jin, H. Xu, B. Li, Multicast scheduling with cooperation and network coding in cognitive radio networks, in: IEEE Conference on Computer Communications (INFOCOM), 2010, pp. 1–9.
[21] P. Auer, N. Ceas-Bianchi, Y. Freund, R.E. Schapire, The nonstochastic multiarmed bandit problem, SIAM J. Comput. 32 (1) (2003) 48–77.
[22] B. Shrader, N.M. Jones, Systematic wireless network coding, in: IEEE Military Communcations Conference (MILCOM), 2009, pp. 1–7.
[23] N. Baldo, A. Asterjadhi, M. Zorzi, Dynamic spectrum access using a network coded cognitive control channel, IEEE Trans. Wireless Commun. (TWC) 9 (8) (2010) 2575–2587.
[24] L. Geng, Y.C. Liang, F. Chin, Network coding for wireless ad hoc cognitive radio networks, in: IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), 2007, pp. 1–5.
[25] A. Asterjadhi, N. Baldo, M. Zorzi, A distributed network coded control channel for multi-hop cognitive radios, IEEE Netw. 23 (4) (2009) 26–32.
[26] H. Almasaeid, A. Kamal, Exploiting multichannel diversity for cooperative multicast in cognitive radio mesh networks, IEEE/ACM Trans. Netw. (ToN) 22 (3) (2014) 770–783.
[27] C.-H. Huang, Y.-C. Lai, K.-C. Chen, Network capacity of cognitive radio relay network, Phys. Commun. 1 (2008) 112–120.
[28] S. Wang, Y.E. Sagduyu, J. Zhang, J. Li, Spectrum shaping via network coding in cognitive radio networks, in: IEEE Conference on Computer Communications (INFOCOM), 2011, pp. 396–400.
[29] A. Fanous, Y.E. Sagduyu, A. Ephremides, Reliable spectrum sensing and opportunistic access in network-coded communications, IEEE J. Sel. Areas Commun. (JSAC) 32 (3) (2014) 400–410.
[30] S. Wang, Y.E. Sagduyu, J. Zhang, J. Li, The impact of induced spectrum predictability via wireless network coding, IEEE Trans. Veh. Technol. (TVT) 61 (2) (2012) 758–769.
[31] Z. Shu, J. Zhou, Y. Yang, H. Sharif, Y. Qian, Network coding-aware channel allocation and routing in cognitive radio networks, in: IEEE Global Communications Conference (Globecom), 2012, pp. 5590–5595.
[32] X. Zhong, Y. Qin, Y. Yang, L. Li, CROR: coding-aware opportunistic routing in multi-channel cognitive radio networks, in: IEEE Global Communications Conference (Globecom), 2014, pp. 100–105.
[33] L. Yang, Y.E. Sagduyu, J. Li, Adaptive network coding for scheduling real-time traffic with hard deadlines, in: ACM MOBIHOC'12, 2012, pp. 105–114.
[34] I.H. Hou, P.R. Kumar, Broadcast delay-constrained traffic over unreliable wireless links with network coding, ACM MOBIHOC'11, 2011.
[35] R. Li, H. Gangammanavar, A. Eryilmaz, Optimal dynamic coding-window selection for serving deadline-constrained traffic over time-varying channels, IEEE Trans. Inf. Theory 58 (10) (2012) 6556–6571.
[36] H. Gangammanavar, A. Eryilmaz, Dynamic coding and rate-control for serving deadline-constrained traffic over fading channels, in: IEEE International Symposium on Information Theory (ISIT), 2010, pp. 1788–1792.
[37] I.H. Hou, P.R. Kumar, Real-time communication over unreliable wireless links: a theory and its applications, IEEE Wireless Commun. 19 (1) (2012) 48–59.
[38] Y. Liu, L.X. Cai, X. Shen, Spectrum-aware opportunistic routing in multi-hop cognitive radio networks, IEEE J. Sel. Areas Commun. (JSAC) 30 (10) (2012) 1958–1968.
[39] H. Kim, K.G. Shin, Efficient discovery of spectrum opportunities with MAC-layer sensing in cognitive radio networks, IEEE Trans. Mob. Comput. (TMC) 7 (5) (2008) 533–545.
[40] Q. Zhao, L. Tong, A. Swami, Y. Chen, Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: a POMDP framework, IEEE J. Sel. Areas Commun. (JSAC) 25 (3) (2007) 589–600.
[41] T. Ho, R. Koetter, M. Médard, E. Effros, J. Shi, D. Karger, A random linear network coding approach to multicast, IEEE Trans. Inf. Theory 52 (10) (2008) 4413–4430.
[42] J. Shao, Mathematical Statistics, Springer, 2003. ISBN: 978-0-387-95382-3
[43] Y.-C. Liang, Y. Zeng, E. Peh, A.T. Hoang, Sensing-throughput tradeoff for cognitive radio networks, IEEE Trans. Wireless Commun. 7 (4) (2009) 1326–1337.
[44] Y.-C. Liang, K.-C. Chen, G.Y. Li, P. Mähönen, Cognitive radio networking and communications: an overview, IEEE Trans. Veh. Technol. 60 (7) (2011) 3386–3407.

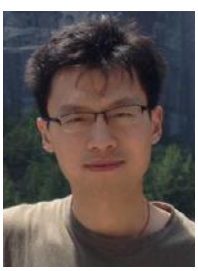
Yuben Qu received the B.S. degree in Mathematics and Applied Mathematics from Nanjing University, and both the M.S. degree in Communication and Information Systems and the Ph.D degree in Computer Science and Technology from PLA University of Science and Technology, in 2009, 2012 and 2016, respectively. He is currently a research assistant in Rocket Force University of Engineering. His research interests include D2D communication, traffic offloading, network coding, cross-layer optimization, cognitive radio networks and stochastic network optimization.



Chao Dong received his Ph.D degree in Communication Engineering from PLA University of Science and Technology, China, in 2007. From 2008 to 2011, he worked as a post Doc at the Department of Computer Science and Technology, Nanjing University, China. He is now an associate professor at the College of Communication Engineering, PLA University of Science and Technology. His research interests include wireless cognitive networks, software defined networks and network coding, etc. He is a member of IEICE and IEEE.

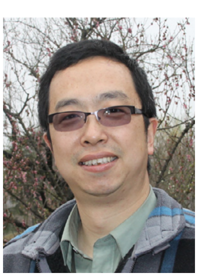


Chen Chen received both the B.S. degree in Communication and Information Systems and the Ph.D degree in Computer Science and Technology from PLA University of Science and Technology, in 2008 and 2014, respectively. His research interests include wireless network coding and network optimization.



Shaojie Tang is an Assistant Professor in the Department of Information Systems at University of Texas at Dallas. He received his Ph.D degree from Department of Computer Science at Illinois Institute of Technology in 2012. He received B.S. in Radio Engineering from Southeast University, P.R. China in 2006. He is a member of IEEE. His main research interests focus on wireless networks (including sensor networks and cognitive radio networks), social networks, security and privacy, and game theory. He has served on the editorial board of Journal of Distributed Sensor Networks. He also served as TPC member of a number of conferences such as ACM MobiHoc, IEEE ICNP and IEEE SECON.

Haipeng Dai is a research assistant in the Department of Computer Science and Technology in Nanjing University, Nanjing, China. He received the B.S. degree in the Department of Electronic Engineering from Shanghai Jiao Tong University, Shanghai, China, in 2010, the Ph.D. degree at the Department of Computer Science and Technology in Nanjing University, Nanjing, China, in 2014. His research interests are mainly in the areas of wireless sensor networks, wireless power transfer and smartphone.



Hai Wang received his Ph.D degree in Communications Engineering from PLA University of Science and Technology, China, in 1999. He is now a professor at the College of Communications Engineering, PLA University of Science and Technology. His current research interests include wireless network, cognitive network and network coding. He was the publication chair of Wireless Communications and Signal Processing (WCSP) 2011. He is a senior member of IEEE.

Chang Tian received his B.S. Degree in communication and information system, M.S.degree and Ph.D. degree in computer science and engineering from Institute of Communications Engineering, Nanjing, China, in 1984, 1989 and 2001, respectively. During September 1995 to September 1996, he was a visiting scholar in Universit di Pisa of Italy. He is currently a professor at the PLA University of Science and Technology, China. He has published widely in the areas of distributed system, wireless ad-hoc network, signal processing for communications, information theory. His current research interests include wireless sensor network, network coding, etc.