

# Intelligent cognitive spectrum collaboration: Convergence of spectrum sensing, spectrum access, and coding technology

Peixiang Cai\* and Yu Zhang

**Abstract:** For a future scenario where everything is connected, cognitive technology can be used for spectrum sensing and access, and emerging coding technologies can be used to address the erasure of packets caused by dynamic spectrum access and realize cognitive spectrum collaboration among users in mass connection scenarios. Machine learning technologies are being increasingly used in the implementation of smart networks. In this paper, after an overview of several key technologies in the cognitive spectrum collaboration, a joint optimization algorithm of dynamic spectrum access and coding is proposed and implemented using reinforcement learning, and the effectiveness of the algorithm is verified by simulations, thus providing a feasible research direction for the realization of cognitive spectrum collaboration.

**Key words:** cognitive radio; spectrum sensing; dynamic spectrum access; coding technology; reinforcement learning; joint optimization

## 1 Introduction

Internet of Everything has become an important development trend of current information and communication technology. In addition to traditional mobile phones and other mobile communication equipments, small appliances at home and vehicles on the road can and must be connected to form a network to serve our lives more intelligently. The concept of Internet of Things (IoT) has also emerged from this trend. Through various information sensors, radio frequency identification technologies, positioning technologies, etc., the real-time collections of objects

or processes that need to be monitored, connected, and interacted with have been realized to obtain all kinds of required information. Thus, by accessing various possible networks, the ubiquitous connection among things is implemented to realize the intelligent perception, identification, and management of goods and processes<sup>[1–4]</sup>.

IoT is an information platform based on the Internet and traditional telecommunications networks that allows all items appearing in our life to form an interconnected network as shown in Fig. 1. IoT has received extensive attention and research in recent years. As one of the three major application scenarios linked to the 5G deployment, the IoT scenario has been gradually developed to

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Manuscript received: 2020-02-26; accepted: 2020-06-09

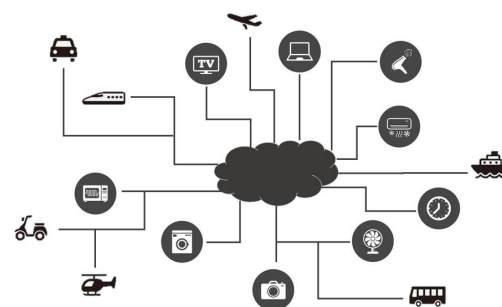
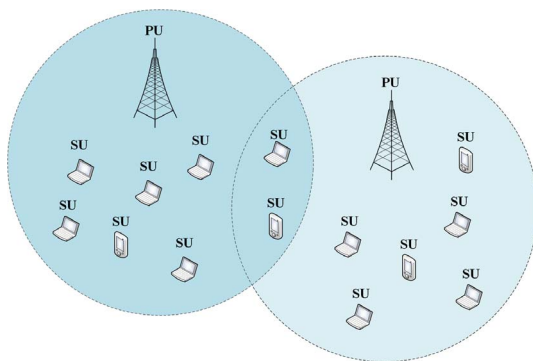


Fig. 1 Application scenarios of the IoT.

serve our lives<sup>[5,6]</sup> and this has further promoted the development of intelligent networks, including wireless sensor networks<sup>[7]</sup> and vehicle networks<sup>[8]</sup>.

However, a scenario where everything is interconnected generates higher demands on the use of spectrum resources, making these limited spectrum resources increasingly scarce. In a scenario of massive connections, how to make devices in a network acquire the spectrum reasonably and realize the communication requirements of the network has become the main challenge to be addressed in intelligent networks. For a distributed network with a large number of users, the available spectrum resources of each user are different. To achieve low latency levels, a centralized implementation using a preset infrastructure often faces difficulties.

In addition, most of the existing frequency bands have been licensed to corresponding services. The frequency bands available for IoT devices to access are very limited, and due to the need to access a massive number of devices, the competition for using this resource is fierce. In addition, in recent years, the annual growth rate of wireless data transmission has reached 50%, which means that it is increasingly impossible for various wireless technologies to acquire licensed frequency bands. Instead, they should share the available spectrum. However, there is currently no effective solution. Some studies have shown that the use of some licensed spectra is relatively low<sup>[9,10]</sup>. Mitola and Maguire<sup>[11]</sup> proposed the concept of Cognitive Radio (CR) on the basis of software radio in 1999. As shown in Fig. 2, its main concept is to achieve opportunistic dynamic spectrum



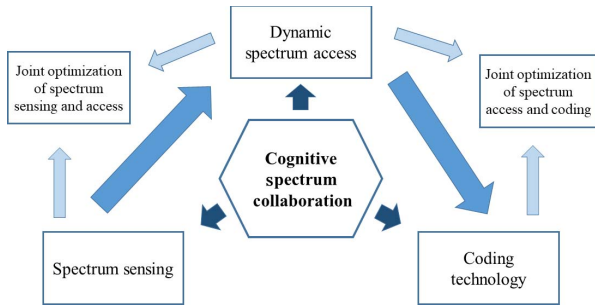
**Fig. 2** Cognitive radio scheme, where SU represents secondary user and PU represents primary user.

access, that is, unauthorized users (also called SUs or cognitive users) carry out spectrum sensing and opportunistically access idle frequency bands originally granted to the licensed users (or PUs) but are rarely used or even unused for the time being. Once the PU is detected and reacquires the frequency band, the SUs should quickly vacate the channel<sup>[12,13]</sup>. At the current stage of spectrum sharing, a simple “perceive and avoid” method is used to avoid interference. However, with the current intensive use of the spectrum, this simple method cannot effectively solve the problem.

To promote research on spectrum utilization, in 2016, the Defense Advanced Research Projects Agency (DARPA) held a three-year Spectrum Collaboration challenge (SC2), which provided new scenarios and ideas for spectrum use in smart networks<sup>[14,15]</sup>, i.e., cognitive spectrum collaboration. In the scenarios of SC2, Base Stations (BSs) and other preset infrastructures are unavailable. Nodes controlled by players in the competition are required to collaborate with each other. They aimed to achieve maximum spectrum utilization and avoid causing interference to some existing PUs in the network coverage area. On the basis of traditional CR technology, this challenge aims to combine the rapid development of machine learning technology and emerging coding technology to achieve cognitive spectrum collaboration. In a demonstration held by SC2 in December 2018, the performance of cognitive spectrum collaboration based on artificial intelligence was 50% higher than that of a human spectrum manager.

Different from traditional CR technology, which mainly focuses on improving sensing ability and obtains more opportunity to access idle spectra, the research of cognitive spectrum collaboration also focuses on the implementation of collaboration after sensing. As shown in Fig. 3, the collaboration includes cooperation among SUs in spectrum sensing, cooperative spectra utilization using dynamic spectrum access technology, and cooperative data transmission using emerging coding technology.

Hence, in this paper, we review the development of several key technologies in cognitive spectrum collaboration, namely, spectrum sensing technology, dynamic spectrum access technology, and emerging



**Fig. 3** Research on cognitive spectrum collaboration.

coding technologies. In addition, we introduce our related work on the joint optimization of dynamic spectrum access technology and coding technology. For scenarios where the PUs' activities result in the dynamic channel erasure probability in the transmission links, the traditional coding technologies with fixed parameters cannot achieve satisfactory performance. Hence, we model the joint optimization problem of dynamic spectrum access technology and coding technology in this paper. Then, a reinforcement learning-based algorithm is proposed to obtain the spectrum access scheme which aims to maximize the reachable rate at the destination node, and the superior performance of the proposed algorithm is verified in the typical single-path unicast scenarios.

In summary, the main contributions of this paper are organized as follows.

First, this paper gives an overview of the development of spectrum sensing technology, dynamic spectrum access technology, and emerging coding technologies in the field of intelligent cognitive spectrum collaboration.

Second, this paper models the joint optimization problem of dynamic spectrum access and forward error correction codes design in cognitive spectrum collaboration scenario, and proposes a reinforcement learning-based algorithm to obtain the optimal spectrum access scheme, whose effectiveness is verified and validated by the simulation in the typical single-path unicast scenarios. To the best of our knowledge, this paper serves as the first work of using reinforcement learning for joint optimization of dynamic spectrum access and forward error correction codes design in the intelligent cognitive spectrum collaboration scenarios.

In addition, this paper points out some future research

topics in the field of intelligent cognitive spectrum collaboration.

The rest of the paper is organized as follows. In Section 2, we introduce the development of spectrum sensing technologies. In Section 3, we offer an overview of dynamic spectrum access technology. An introduction to emerging coding technologies is shown in Section 4. The modeling of the joint optimization of dynamic spectrum access and coding is introduced in Section 5, and the proposed algorithm is described in detail in Section 6. In Section 7, we conduct simulation and analyze the results, and in Section 8, we summarize this paper and outline directions for future research.

## 2 Spectrum sensing technology

### 2.1 Spectrum sensing

Spectrum sensing technology is the basis of cognitive technology. For unknown spectrum situations, users in the intelligent network need to perceive the spectrum and find free spectra for utilization. Reducing interference to higher priority users, such as in the typical CR scenario, SUs opportunistically access the licensed spectrum currently not used by the PUs. When there is an error in the result of spectrum sensing, there may be false alarms or miss detections. False alarms will cause SUs to lose the opportunity to access the spectrum and reduce the network throughput. Miss detections will cause SUs to access the unavailable spectrum and that may interfere against PUs. This may punish the SUs, and the SUs may even be prohibited from using the licensed spectrum of the PUs again. Therefore, avoiding miss detection and improving the sensing accuracy are the main purposes of spectrum sensing technology.

Spectrum sensing technology mainly includes narrowband spectrum sensing and wideband spectrum sensing. Generally, narrowband spectrum sensing aims to obtain the status of a single spectrum at a time, whereas wideband spectrum sensing analyzes a wide frequency band whose bandwidth generally exceeds the coherence bandwidth of the channel<sup>[16]</sup>.

Wideband spectrum sensing can be categorized into Nyquist sampling-based sensing and sub-Nyquist sampling-based sensing. The former one uses standard

analog to digital converters to obtain the wideband signal for analyzing the spectrum status. The latter one uses sampling rates lower than the Nyquist sampling rates through some technologies including compressive sensing<sup>[16]</sup>.

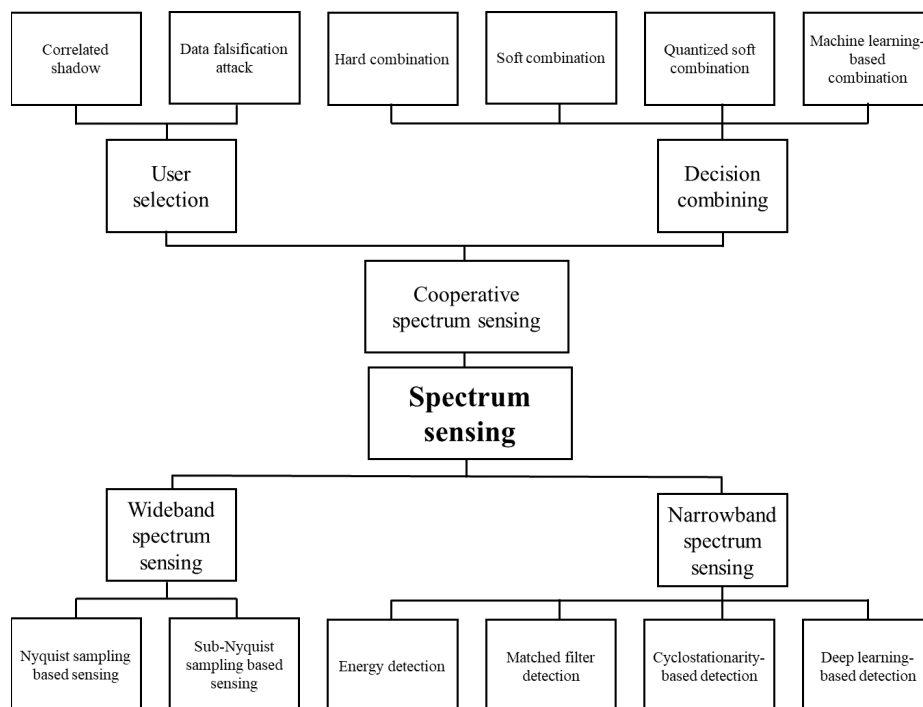
We mainly focus on narrowband spectrum sensing in the following part of this paper. As shown in Fig. 4, classic narrowband spectrum sensing methods include energy detection<sup>[17–20]</sup>, matched filter detection<sup>[21–23]</sup>, and cyclic stationary detection<sup>[24–27]</sup>. Energy detection has become the most popular type of spectrum sensing because it requires less prior information from the PUs and is simple to implement. The main concept is to measure the energy of the signal in the detected spectrum over a period of time and compare it with the preset decision threshold. When the energy value is higher than the decision threshold, there exists a nearby PU using the spectrum to communicate or provide other services; otherwise, the spectrum is not occupied by the PU, or the PU occupying the spectrum is far away; hence, the SU's access to the spectrum will not cause interference with the PU. In the energy detection method, the selection of the decision threshold is very important. When the decision threshold is set high, the false alarm rate is low, but the miss detection rate is high; otherwise, the false

alarm rate is high, and the miss detection rate is low<sup>[28]</sup>. These criteria must be integrated into the balance to set a proper threshold.

When the complete information of the PU signal is known, a matched filter detection method can be adopted. The principle is to perform a self-correlation operation between the known PU signal and the detected signal and set a correlation threshold for judgment. This type of methods can theoretically achieve the best performance in an additive white Gaussian noise channel, but the requirement of the PU signal information limits its applications.

Cyclostationary detection uses the periodicity of the mean value of the modulated PU signal and the autocorrelation function to perform autocorrelation on the detected signal and makes a decision based on the correlation characteristics of the cyclic spectral density function. The trade-off between performance and complexity lies in somewhere between the above two methods.

In recent years, with the development of artificial intelligence technology, academia has also begun to use deep learning technology for wireless signal recognition<sup>[29]</sup>. Furthermore, there have been attempts to use neural networks for spectrum sensing problems in



**Fig. 4 Key technology of spectrum sensing.**

intelligent networks that have achieved good results<sup>[30,31]</sup>.

## 2.2 Cooperative spectrum sensing

To improve the speed and accuracy of perception, the information interaction of perception results can be performed between SUs to obtain higher perception accuracy. This method is called cooperative spectrum sensing<sup>[32]</sup>. Cooperative spectrum sensing is one of the key technologies of cognitive spectrum collaboration. The study of cooperative spectrum sensing mainly involves the following aspects.

The first aspect is the choice of cooperative spectrum sensing neighbors. In some cooperative spectrum sensing scenes, SUs request other users to perform spectrum sensing to improve the accuracy of their own decision results, but the energy consumed by spectrum sensing and the improved accuracy should be compromised. In other cooperative spectrum sensing scenes, SUs use only the sensing results of neighbors who would have to perceive the spectrum to fuse. Since the neighbors of SUs may suffer from shadow fading and malicious users may exist as shown in Fig. 5<sup>[33]</sup>, the fusion of the perception results of all neighbors is often not the best result. In addition, the communication overhead caused by the interaction perception results is also a problem to be considered. The method of reinforcement learning has often been used in the related work of neighbor selection for cooperative spectrum sensing in recent years. Reference [34] adopted a centralized reinforcement learning method to solve the problem of cooperative spectrum sensing under related fading. In Ref. [35], the value function approximation method was used to reduce the detection complexity so that the distributed reinforcement learning method is available in large networks. Reference [36] adopted deep reinforcement learning, which uses neural networks to

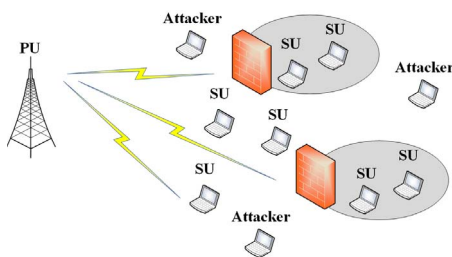


Fig. 5 Cooperative spectrum sensing scheme.

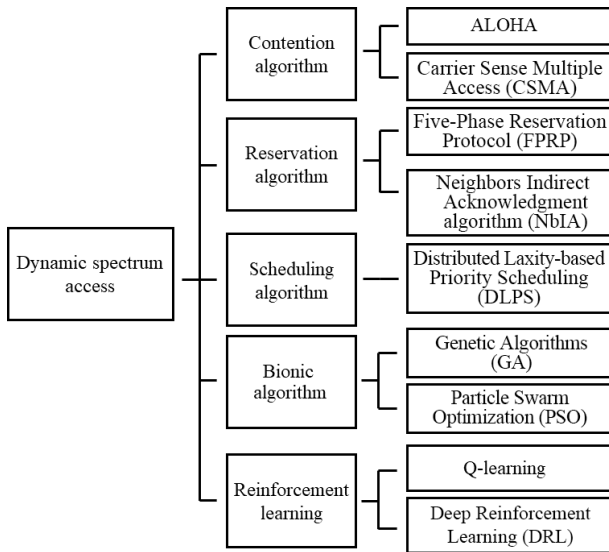
achieve a more intelligent value function approximation.

The second aspect is the judgment of perceived results. For example, in energy detection, the perception result sent by the user can only be a binary decision result (hard decision) of 0 or 1<sup>[37]</sup> or a more detailed detected energy value (soft decision)<sup>[38]</sup>. Generally, the more information transmitted, the better the accuracy of the final decision. Therefore, transmitting information is a compromise between perceived accuracy and communication overhead<sup>[39]</sup>. When making judgments, the typical methods include majority judgment and K/N judgment<sup>[40]</sup>. In recent years, machine learning has also been used to make judgments and can achieve better judgment accuracy by reducing the required transmission information<sup>[41–43]</sup>.

## 3 Dynamic spectrum access technology

For intelligent network scenarios with massive access, spectrum resources are one of the most important resources. On the basis of performing spectrum sensing to obtain free spectra, it is also necessary to allocate spectrum resources efficiently. The SUs need to achieve collaboration to reduce collisions when using the spectrum resource. Besides, due to the large number of users in the intelligent network, the changes in user requirements for spectrum resources are becoming increasingly complicated<sup>[44]</sup>. On the basis of traditional authorized spectrum access, it is also necessary to introduce intelligent dynamic spectrum access technology to improve spectrum utilization<sup>[45]</sup>. In addition, the goal of dynamic spectrum access is often not just to maximize network throughput. Depending on the scenario, issues, such as QoS, data priority, and fairness, need to be considered. A brief summary on classic dynamic spectrum access algorithms is given in Fig. 6.

In a single-hop network with a central node or a BS, the BS can allocate the spectrum that each node accesses and it is easy to implement spectrum access. However, intelligent networks are often multihop networks, facing problems such as hidden and exposed terminals, and in many related scenarios, spectrum access cannot be achieved by using preset infrastructure such as BSs. To solve the problem of spectrum access in dynamic



**Fig. 6 Research on dynamic spectrum access.**

networks, many methods can implement dynamic spectrum access, including competition algorithms (such as ALOHA<sup>[46]</sup> and CSMA<sup>[47]</sup>), reservation algorithms (such as FPRP<sup>[48]</sup> and NbIA<sup>[49]</sup>), and the queuing algorithms (such as DLPS<sup>[50]</sup>). With the development of evolutionary algorithms, including GA<sup>[51,52]</sup>, PSO<sup>[53]</sup>, and biological foraging algorithms<sup>[54]</sup>, researchers are increasingly trying to integrate their use in dynamic spectrum access.

The above algorithms are suitable for different scenarios. Competition algorithms are mainly used in noncooperative scenarios. Users cannot achieve good coordination through effective information exchange. Therefore, the efficiency of spectrum access is low, but related communication overhead is not required. The class of reservation algorithms needs to achieve the spectrum reservation by reservation requests and confirmation in the control channel and thus reduce collisions in data channels. The basic concept of the evolutionary algorithm is to model the dynamic spectrum access problem as an optimization problem with a certain prior knowledge of the network topology. In actual scenarios, neighbor discovery and control information interactions are used, and then the network topology can be obtained in a short time when the topology does not change quickly.

In the cognitive scenario, the dynamic spectrum access problem is more complicated because the activity of

the PUs is constantly changing<sup>[55]</sup>. When the sensing ability is sufficient, some algorithms can converge quickly to allocate the available spectrum in every slot. However, with the general design of slot structures in cognitive scenarios, spectrum sensing and spectrum access are often processed jointly. SUs need to determine the perceived spectrum and access the perceived idle spectrum. Then, selecting a spectrum with a high probability of being sensed as idle based on past sensing results enables SUs to obtain the better available spectrum for communication. In this type of problem, the technology of reinforcement learning shows its applicability.

In reinforcement learning, each SU acts as an agent and selects actions based on the current spectrum environment conditions. Each agent selects a sensing and access scheme for execution in its own action and calculates the reward of this action based on the results of the execution to learn how to choose the best strategy for action in different environments<sup>[56-59]</sup>. According to different access requirements, different reinforcement learning uses different reward functions. In addition, for scenarios with a large number of users, to improve the convergence speed of learning algorithms, in addition to using the linear combination of feature vectors to fit the Q-table in Q-learning as described in Ref. [56], the DRL proposed by combining deep learning and reinforcement learning is also used to implement dynamic spectrum access in cognitive scenarios<sup>[60]</sup>. In other works, such as Ref. [61], the power control and dynamic spectrum access are combined and optimized.

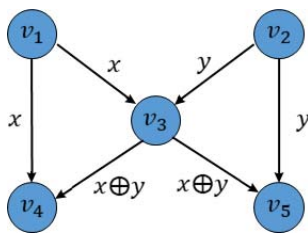
## 4 Coding technology

Coding technology, as an important means to deal with errors and erasure in link transmission, has become the key to ensuring the successful rate of communication and the efficient use of spectrum resources. In addition to Low-Density Parity-Check (LDPC) codes, turbo codes, and other coding technologies that have been widely used, some emerging coding technologies can also play a role in the cognitive spectrum collaboration scene due to their unique characteristics. Most of the networks in the cognitive scenario are multihop broadcast networks. In these networks, network coding technology can be

used to realize the collaboration between source users and relay users to improve the network throughput rate, while the overhead problems from a large number of retransmission in broadcast networks can be solved by the implementation of fountain codes and multiple users can cooperatively transmit data using fountain codes. In addition, although machine learning can obtain better throughput performance in a very dynamic environment, such as the cognitive spectrum collaboration scene, due to changes in environmental conditions, such as interference from the PU, there is a change in performance during the learning process, and the collision probability of data packet transmission on the link also changes dynamically, resulting in a probability of dynamic channel erasure. The ability of fountain codes and network codes to cope with dynamic erasure channels also makes them suitable for use in cognitive spectrum collaboration scenarios. In this section, we introduce network coding, fountain codes, and Batch Sparse (BATS) codes based on them.

#### 4.1 Network coding

Different from source coding which compresses information at the source to improve transmission efficiency and channel coding which achieves reliable transmission in noisy channels by increasing redundancy, network coding technology has been greatly developed in recent years<sup>[62-66]</sup>. Relay nodes in traditional networks are responsible for forwarding and routing. As shown in Fig. 7, network coding allows relay nodes in the network to re-encode the received packets, making the network throughput approach the bound of the maximum flow minimum cut. Compared with traditional multicast routing, network coding realizes the collaboration



**Fig. 7 Typical network coding scheme.** Nodes  $v_1$  and  $v_2$  need to send packets  $x$  and  $y$  to nodes  $v_4$  and  $v_5$ . When the relay node  $v_3$  can re-encode the received packets, the network throughput can be improved.

of users, thus greatly improves the communication efficiency of networks.

The early work of network coding mainly focused on finding coding methods that approximated the maximum flow boundary of the network when the network topology was known and thus proposed a series of works concerning linear network coding<sup>[67,68]</sup>, such as linear code multicast. Random linear network coding is widely used as one of the simplest forms of network coding<sup>[69]</sup>. By performing a random linear combination of data packets and the transfer of coefficient vectors at the relay nodes, it can deal with unknown network topologies. In addition, there are also studies on variable rate linear network coding<sup>[70]</sup> and network coding in undirected graphs<sup>[71]</sup>. Subsequently, convolutional network codes were proposed to address the looped network structure<sup>[72]</sup>. Because network coding also has the ability to cope with random errors and erasure channels, the research branch of network error correction codes has also been developed<sup>[73]</sup>. Although network coding improves network throughput, the encoding and decoding at the relay nodes create additional computing and storage costs.

#### 4.2 Fountain code

As the spectrum utilization condition becomes more complex, the channel conditions in communication systems are often in a dynamic state. Under these conditions, the forward error correction code with a fixed rate often cannot achieve higher efficiency. A fountain code, as an emerging rateless coding technology, can deal with the dynamically changing channel erasure probability in the erasure channel. Therefore, it is suitable for the channel erasure scenario caused by packet conflicts. A fountain code can also be used in noise channels where the signal-to-noise ratio changes dynamically when it is concatenated with error correction codes with good performance.

The concept of a fountain code was first proposed by Byers et al.<sup>[74]</sup> in 1998. The fountain code is named for its implementation. The information to be sent in the fountain code is first divided into multiple original data packets, and then it randomly selects a certain number of data packets (determined by a specially designed degree

distribution function) to perform a bitwise eXclusive-OR (XOR) operation to obtain encoded data packets. When the total number of data packets received is slightly larger than the number of original data packets, the original data can be successfully decoded with a high probability. This encoding method can create an infinite number of encoded data packets, similar to water droplets that are constantly generated by a fountain. In addition, it is similar to the process of receiving water using a bucket. As long as a sufficient number of water droplets are received, the original data packet can be restored. Hence, this encoding method is vividly named the fountain code. From the above description, it can also be seen that the fountain code does not need a retransmission mechanism and multiple users can cooperatively complete data transmission using fountain code. The senders can continue to generate encoded packets for transmission until the receiver feeds back the information of the finished decoding. Due to this characteristic of the fountain code, it is also particularly suitable for erasure channels in broadcasting schemes.

In the development process of fountain codes, there are several classic coding methods, such as random linear fountain codes, Luby Transform (LT) codes, and Raptor codes. The random linear fountain code generates a random sequence at each encoding and performs weighted summation on the original data packet according to the random sequence to obtain the encoded data packet. Reference [75] proved that for this encoding method, with the growth of the number of received data packets, the probability of successfully recovering all original data packets tends to 1, and when the number of original data packets is infinite, the additional overhead is negligible, so the performance of random linear fountain code can approach the theoretical bound. However, the decoding process of the random linear fountain code involves matrix inversion, and the number of calculations is to the third power of the number of original packets, so it is difficult to be used in practical applications.

The LT code is an improvement on the random linear fountain code. The sparse graph coding concept is used to greatly reduce the complexity of encoding and decoding, making the fountain code practical. The

LT code randomly selects a degree from the designed degree distribution function and then uniformly and randomly selects a corresponding number of packets from the original data packet to perform a continuous bitwise XOR operation to obtain the encoding results<sup>[76]</sup>. When the states of the random sequence generators at the transmitting and receiving ends are consistent, the transmission overhead of the coefficients can also be reduced. The average value of the designed degree distribution function is much smaller than the number of packets. It is a sparse graph code that can be decoded by belief propagation based on the Tanner graph. The degree distribution function in the LT code uses the robust soliton degree distribution. Many works have subsequently improved the degree distribution and proposed fountain codes suitable for different scenarios<sup>[77-79]</sup>.

Because the average degree of the LT code is small, the recovery of all original data packets may not be realized due to the loss of some data packets, so it may appear that most of the original data packets have been received when the number of received packets is slightly larger than the number of original data packets, but the remaining small portion of the data packets needs many packets sent overhead to be completely solved. The Raptor code improved the performance of the fountain code by cascading encoding. The Raptor code uses an outer code (such as LDPC code) to pre-encode the original data packet because the LT code has difficulty covering all the original data packets. In addition, the deep learning method is also used to improve the belief propagation algorithm, which improves the decoding efficiency of fountain codes<sup>[80]</sup>.

Fountain codes currently have many practical scenarios. For example, fountain codes can be used in traditional multipath Transmission Control Protocol (TCP) connections to reduce the heterogeneity of different paths<sup>[81]</sup>. Fountain codes also display superior performance in data storage<sup>[82]</sup> and data distribution<sup>[83]</sup> scenarios. In addition, for scenarios where data such as video multicast applications<sup>[84,85]</sup> have different priorities, fountain codes with unequal error protection have also been proposed.

Different from a fountain code with a degree



distribution function preset as described above, the online version of the fountain code has also been developed rapidly to cope with the extreme channel conditions and determine a higher decoding probability degree in the current decoding state through feedback. As a milestone in the field of online fountain codes, the growth code<sup>[86]</sup> guides the encoding process by calculating the degree with the greatest probability that it will encode only one unrecovered symbol with other recovered symbols in the current decoding state. Reference [87] proposed an online fountain code with low decoding overhead, and the online fountain code demonstrated excellent overhead performance. The receiver dealing with the online fountain code can obtain the optimal encoding strategy in the current decoding state. Even in an extreme decoding state due to malicious attacks (which is very different from the decoding state under random loss), good decoding performance can be achieved. However, the online fountain code requires the receiver to feed information back when the optimal encoding degree changes. Therefore, compared with the most classic fountain code (such as the LT code), the online fountain code introduces overhead due to its feedback.

### 4.3 Batched sparse codes

The network in the cognitive scenario is mostly a multihop broadcast network. The performance of network coding in multihop scenarios is better than that of direct routing<sup>[88]</sup>. In addition, fountain codes can achieve better performance than network coding in broadcast scenarios with a large number of users<sup>[89]</sup>. In Ref. [90], the fountain code and random linear network coding were combined to obtain the BATS codes. The outer code part was sampled from the degree distribution using the fountain code form, and then a corresponding number of the original symbol was randomly selected to be used as the batch. These numbers are then multiplied by the generation matrix of the batch. The inner code performs a linear transformation on each batch at the relay node. At the same time, only the symbols that belong to the same batch will be linearly combined at the relay node. The overall effect of the inner code

and channel erasure can be represented by a linear transformation matrix. The operation of the inner code maintains the degree distribution of each batch, and the belief propagation decoding algorithm can decode the inner and outer codes at the same time.

Reference [90] proved that when using batch sparse codes, the rank distribution of the linear transformation matrix determines the maximum achievable rate. For a given rank distribution, a degree distribution that can reach the rate very close to the average rank in the target node can always be found using the method of degree distribution optimization. Many existing studies on BATS codes focus on solving the optimal degree distribution with the known transformation matrix rank distribution. For example, Ref. [91] proposed a greedy method to find the optimal degree distribution for finite original symbols. Reference [92] used prior information on better degree distribution to greatly reduce the number of optimization variables.

Research on how to optimize the rank distribution to increase the maximum achievable rate has also attracted the attention of academia. The performance of the random scheduling method in standard batch sparse codes is poor. In several works, the optimization problem was modeled by limiting the maximum number of packets sent at the relay node<sup>[93,94]</sup>. Using an adaptive scheduling framework, each network node adaptively adjusts the number of packets according to its own status. Other works improved efficiency by optimizing the packet number that a relay node re-encodes each batch. Reference [95] optimized the number of encoded packets of a relay node in a unicast stream in a multihop wireless network. The noniterative form of the optimization problem is obtained by means of value decomposition, and then the continuous relaxation of the nonlinear integer programming problem is performed. The optimization problem is solved by using common solutions to the nonlinear programming problem. The model proposed in Ref. [96] assumed that the broadcast nature of wireless communication can enable nodes to overhear. Under this model, an adaptive re-encoding framework is adopted to increase the achievable rate under the limitation of the average channel usage times.

## 5 Joint optimization of spectrum access and coding

Generally, machine learning-based intelligent spectrum access methods could achieve better throughput performance in a dynamic spectrum environment. However, the performance of machine learning methods during the learning process is varying drastically. Besides, due to the changes in environmental conditions, such as PU interference, the number of collisions in spectrum access results is dynamic, which results in dynamic channel erasure probability.

Besides, when information is transmitted in a multihop network, such as in cognitive spectrum collaboration schemes, because different links have different erasure probabilities, when spectrum resources are limited, allocating equal spectrum resources to all links cannot allow information to reach the destination node as quickly as possible. The BATS codes, which combine the fountain codes with the network coding, are rateless codes. It performs better than traditional fountain codes in multi-hop networks. Therefore, we choose to investigate the application of BATS in intelligent spectrum collaboration scenarios in this paper. In BATS codes, the rank distribution of the linear transformation matrix in the destination node determines the maximum achievable rate of the network. Therefore, optimizing the rank distribution can increase the maximum rate. In this section, we study how to optimize the rank distribution of the linear transformation matrix to provide different nodes with unequal transmission opportunities when the network allocates spectrum.

The BATS code is composed of an inner code and an outer code. The outer code uses a fountain code in the form of a matrix to encode the original symbols to be transmitted. Each batch contains  $B$  data packets, so the BATS code is rateless.

The inner code performs a linear transformation on each batch, which is represented by a linear transformation matrix. The BATS code uses its rateless property to solve the feedback problem in a sequential scheduling of block codes. The BATS code also solves the degree distribution problem of methods based on fountain code classes because the inner code of the

BATS code does not change the degree distribution of the batch. The rank distribution of a batch of linear transformation matrices plays an important role in the BATS code. The optimization of outer codes depends only on rank distribution.

Assume the original data are  $\mathbf{B} = [b_1, b_2, \dots, b_K]$ , and the  $i$ -th batch is generated from the subset  $\mathbf{B}_i \subset \mathbf{B}$  by  $\mathbf{X}_i = \mathbf{B}_i \mathbf{G}_i$ , where  $\mathbf{G}_i$  is the generation matrix of the  $i$ -th batch and has  $B$  columns. The BATS code then selects  $\mathbf{B}_i$  in the form of a fountain code. Specify a degree distribution of  $\Psi = (\Psi_0, \Psi_1, \dots, \Psi_K)$ , sample the degree distribution each time a batch is generated, obtain  $d_i$  with the probability of  $\Psi_i$ , and then randomly and uniformly select  $d_i$  original data from  $\mathbf{B}$  to form  $\mathbf{B}_i$ .

Let  $\mathbf{H}_i$  be the linear transformation matrix of the  $i$ -th batch; then the  $i$ -th batch received at the target node is  $\mathbf{Y}_i = \mathbf{X}_i \mathbf{H}_i = \mathbf{B}_i \mathbf{G}_i \mathbf{H}_i$ . From this result, the following Tanner graph can be constructed, as shown in Fig. 8.

When the belief propagation algorithm is used for decoding, the check node  $i$  can be solved when  $\text{rank}(\mathbf{G}_i \mathbf{H}_i) = d_i$ , so all the data in  $\mathbf{B}_i$  can be obtained by solving the linear equation system  $\mathbf{Y}_i = \mathbf{X}_i \mathbf{H}_i = \mathbf{B}_i \mathbf{G}_i \mathbf{H}_i$ . Afterwards, the value of the obtained input data packet can be replaced in the batch that is not solved in the Tanner graph.

As shown in Fig. 9, a path from the source node to the destination node has been established in the following analysis. The research on single-path unicast scenarios can be extended to general multipath unicast scenarios and some multicast scenarios.

We independently analyze the transmission of each batch. The source node transmits  $t_1$  packets of a batch on  $(v_1, v_2)$ . If node  $v_k$  receives at least one packet, it performs random linear encoding on these packets to

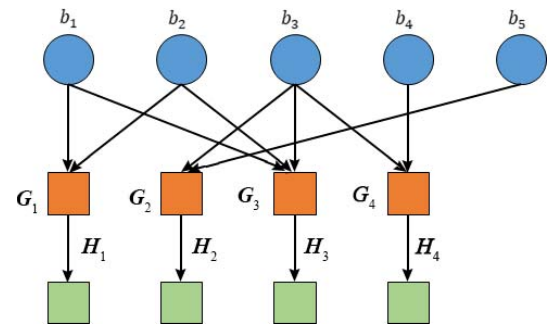
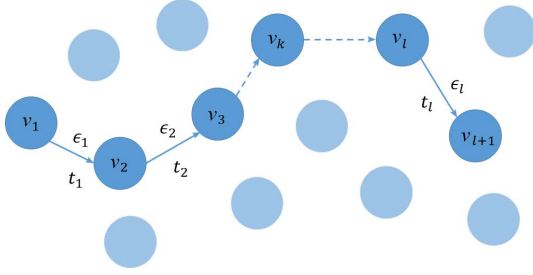


Fig. 8 Tanner graph of BATS codes.



**Fig. 9** Example of single-path unicasts. Source node  $v_1$  transmits some data to the destination node  $v_{l+1}$  through relay nodes  $v_2, v_3, \dots, v_l$ . Channel erasure probability in the link  $(v_1, v_2)$  is  $\epsilon_1$  and the number of transmitted packets in this link is  $t_1$ .

obtain the  $t_k$  packet for transmissions.

Let  $\mathbf{h}_k = [h_{k,0}, h_{k,1}, \dots, h_{k,B}]$  be the rank distribution of the transmission matrix at node  $v_k$ . The conclusions in Refs. [90, 97] show that the rank distribution of each node can be iteratively obtained by

$$\mathbf{h}_k = \begin{cases} [0, 0, \dots, 1], & k = 1; \\ \mathbf{h}_{k-1} \mathbf{P}_{k-1}, & k > 1 \end{cases} \quad (1)$$

When  $1 \leq j \leq i \leq B + 1$ , the elements of  $\mathbf{P}_k$  are

$$p_k(i, j) = \sum_{n=j-1}^{t_k} \binom{t_k}{n} (1 - \epsilon_k)^n \epsilon_k^{t_k-n} \zeta_{j-1}^{i-1, n} \quad (2)$$

where  $\epsilon_k$  is the channel erasure probability of the  $k$ -th link,

$$\zeta_r^{d, k} = \frac{\zeta_r^d \zeta_r^k}{\zeta_r^q q^{(d-r)(k-r)}} \quad (3)$$

and

$$\zeta_r^m = \begin{cases} \prod_{i=0}^{r-1} (1 - q^{-m+i}), & r > 0; \\ 1, & r = 0 \end{cases} \quad (4)$$

where  $q$  is the size of the finite field of the transmitted symbols. For other  $i$  and  $j$ ,  $p_k(i, j) = 0$ .

When the rank distribution at the target node is  $\mathbf{h}_{l+1}$ , the rate that the outer code can reach is close to  $\bar{h}_{l+1} = \sum_{i=0}^B i h_{l+1, i}$ . The optimization problem searches  $t_1, t_2, \dots, t_l$  to maximize  $\bar{h}_{l+1}$  when the number of spectra is limited. Ignoring the existence of the PU temporarily, we can assume that  $M$  spectra are available at each node. In addition, to simplify the analysis, we limit the neighbors within two hops to share the same spectrum to avoid collisions, although when they share the spectrum, only the intermediate nodes are affected.

Maximizing  $\bar{h}_{l+1}$  obtains the optimization problem:

$$\begin{aligned} & \text{maximize}_{t_1, t_2, \dots, t_l} \bar{h}_{l+1}, \\ & \text{s.t. } t_k \in \mathbb{Z}^+, \sum_{j=k-2}^{k+2} t_j \leq M, k = 1, \dots, l \end{aligned} \quad (5)$$

This problem is a nonlinear integer programming problem. The above model is established in a single-path unicast scenario. As long as the sum of the number of spectra occupied by neighboring nodes within two hops is no more than the number of available spectra  $M$ , a conflict-free access scheme can be created to satisfy  $t_k$  at each hop. If the scenario is not a line network but a complex topology, the problem cannot be simplified as described above because any  $t_k$  that meets the number limitation may not find a conflict-free access scheme (Proof: see Appendix A).

In addition, due to the multihop property, each batch of data packets arrives at the node  $k$  after  $k - 1$  timeslots. Assuming that the number of packets sent by node  $k$  in the  $w$ -th time slot is  $t_k^w$ ,  $\bar{h}_{l+1}^w$  should be calculated using  $t_l^w, t_{l-1}^{w-1}, \dots, t_0^{w-l}$ , and the limitation of the optimization condition becomes  $\sum_{j=k-2}^{k+2} t_j^w \leq M$ . However, it can be proven that when the channel erasure probability of the link remains stable, the max-min criterion is used to ensure fairness between batches without distinguishing the importance of different batches, and then the optimal strategy should be fixed in each slot (Proof: see Appendix B). Therefore, the optimization problem can be reduced to a form of Formula (5).

To solve this optimization problem, NOMAD<sup>[98]</sup> can be used, and the genetic algorithm can obtain an approximate optimal solution. In addition, the method in Ref. [97] can be adopted to continuously relax the optimization problem to obtain a faster solution speed.

## 6 Reinforcement learning based joint optimization of spectrum access and coding

The modeling scenarios in Section 5 use many simplified assumptions, which are not applicable in the context of cognitive spectrum collaboration.

First, for the nodes in a distributed network, not very

much of the network information can be obtained, such as the average erasure probability of each link required in the optimization problem. In the cognitive spectrum collaboration scenario, the erasure probability is not constant, so it is not possible to determine the channel erasure probability of the next slot through the feedback of the previous slot. In addition, the modeling scenario in Section 5 does not consider the cognitive situation in the presence of the PUs. In the cognitive spectrum collaboration scenario, channel erasure is caused not only by factors such as noise and fading but also by the loss of the packets due to the activity of the PUs. When the activity of the PUs follows certain law, the change in the channel erasure probability also follows certain law.

Second, according to the analysis in Section 5, when the channel erasure probability of the link changes dynamically due to the behavior of the PU, the optimal strategy for different batches may be different, so the modeling method proposed in Section 5 is not applicable. The average rank at the target node will depend on the spectrum access results of each node in multiple cycles, which greatly increases the optimization variables of the problem.

In addition, in the case of complex topology, the modeling problem is more complicated than that in the case of a single-path unicast scenario, and joint optimization with spectrum access increases the difficulty of solving optimization problems. If the modeling optimization problem cannot be solved in a short time, it cannot be applied in the actual network.

These reasons led us to abandon modeling the problem as an optimization problem in the cognitive spectrum collaboration scenario; in combination with the above analysis, because the key factor of channel erasure probability is affected by the behavior of the PU, reinforcement learning technology has also recently proven to be an effective method in CR networks, such as selecting the optimal spectrum sensing strategy for different behaviors of the PUs. Hence, we adopt the most popular Q-learning algorithm to obtain a spectrum access strategy that maximizes the average rank distribution at the target node during the learning process. For the sake of intuitiveness, we model our learning problem in a single-path unicast scenario. The proposed algorithm

can be easily extended to general multipath unicast, two-way transmission, and some multicast scenarios.

The nodes, except for the destination node in the network, will use the Q-learning method to learn. We set the state  $s_k$  to be the number of packets sent by the previous and next-hop nodes of node  $k$  in the last slot, and  $s'_k$  is the number of packets sent by the previous and next-hop nodes of node  $k$  in this slot. Because it is a line network, according to the analysis in Section 5, occupying which spectra can be reduced to occupying how many spectra. Nodes can use the method agreed upon when the network was established to occupy the spectrum according to the number. These data do not need information exchange of the control channel and can be obtained directly through the statistics of the received and sent packets in the previous slot. The action  $a_k$  is the number of spectra occupied by node  $k$  in this slot, and the reward  $r_k$  is the average rank at the next-hop node.

This problem is a multiagent reinforcement learning problem. When the channel erasure probability follows a certain rule (such as the Markov process), according to the derivation in Ref. [99], the following iterations of Q-learning can ensure convergence.

$$Q_k(s_k, a_k) = (1 - \alpha_t)Q_k(s_k, a_k) + \alpha_t(r_k + \lambda \max_{a'_k} Q_k(s'_k, a'_k)) \quad (6)$$

where  $\alpha_t \in [0, 1)$  is a parameter that decays with the learning process, and  $\lambda$  is a discount factor, whose value is generally less than 1. The action  $a'_k$  of the next slot can be selected by the method of  $\varepsilon$ -greedy, which is randomly selected with the probability of  $\varepsilon$ , and the action with the highest  $Q$  value in the state  $s'_k$  is selected with the probability of  $1 - \varepsilon$  to be executed.

In addition, under the above model, the action state space is relatively small, but when studying the multihop broadcast situation of the entire network, similar to the analysis in Section 5, the conflict-free spectrum access schemes that meet the number limitation may not be found. Therefore, in the modeling of the learning problem, the state is  $s_k = [s_k^1, s_k^2, \dots, s_k^M]$ , where  $s_k^m = 1$  when the spectra  $m$  are occupied by the previous and next hop of node  $k$  in the last slot, and  $s_k^m = 0$  otherwise. The action is  $a_k = [a_k^1, a_k^2, \dots, a_k^M]$ , where

$a_k^m = 1$  when the spectra  $m$  are occupied by node  $k$  in this slot, and  $a_k^m = 0$  otherwise.

Hence, the state-action space is relatively large. The iteration of Q-learning is modified as follows:

$$Q_k(s_k, \mathbf{a}_k) = (1 - \alpha_t) Q_k(s_k, \mathbf{a}_k) + \alpha_t (r_k + \lambda \max_{\mathbf{a}'_k} Q_k(s'_k, \mathbf{a}'_k)) \quad (7)$$

This kind of problem can introduce technologies, such as deep Q-networks to speed up convergence. This content is not the focus of this paper and will not be discussed.

## 7 Simulation and analysis

We conducted 100 independent experiments under the following settings. Since the sending of packets by each node most directly affects the decision of its neighbors within two hops, we established a six-hop network consisting of seven nodes for simulation. Assume that the average and variance of the erasure probability due to fading and noise from each link are 0.05, 0.05 (low), 0.15, 0.15 (medium), and 0.25, 0.25 (high). Assume that the number of available spectra is  $M = 80$  and the size of the batch is  $B = 10$ .

Each node will send data packets according to the number of spectra allocated to it in this time slot. If node  $k$  is allocated to  $m$  spectra in this time slot, the batch will be encoded into  $m$  data packets. Because the size of each encoded data packets in BATS codes is small, we assume that each time slot is divided into 100 mini-slots. In each mini-slot, the node sends a batch of data to its next-hop node. In the simulation, to further reduce the size of the action space, a value of  $a$  (such as  $a < B$ ) that is too small will cause the number of data packets of the batch to be less than the rank before sending, which will cause the rank distribution at the next-hop node to drop significantly. A large value of  $a$  easily causes conflicts in spectrum access and results in a large number of data packet erasure. Hence, we set the action  $a$  in the Q-learning algorithm to take values from 12 to 20. When the sum of the number of occupied spectra within two hops is greater than  $M$ , the packet sent by some nodes will be randomly erased until the number of successfully sent packets within two hops is not greater than  $M$ .

From the analysis in Section 5, it can be seen that the

results of the optimization problem are closely related to the number of available spectra. We mainly study the situation where the number of available spectra is generally sufficient. When the number of available spectra is large, in a mini-slot, multiple batches can be sent on the available spectrum, and when the number is small, multiple mini-slots can be used to transmit one batch.

We do not specify a specific spectrum sensing method in the simulation. It is assumed that the false alarm and miss detection probability of the spectrum sensing method used in the current environment are both 0.1. The impact of this incorrect detection will lead to an increase in the probability of channel erasure. When an SU uses a spectrum that is actually occupied by the PUs to send a data packet due to miss detection, the next-hop node fails to receive the data packet, and a channel erasure occurs due to the large power of the PUs. False alarm will reduce the amount of spectrum available to SUs.

The behavior of the PUs is modeled as a Markov process. In the simulation, we assume that when the PU occupies the spectrum on the  $k$ -th link in the last slot, the PU will occupy the spectrum on the  $k$ -th link with a probability of 0.8 in this slot and occupy the spectrum on the  $(k + 1)$ -th link with a probability of 0.2. The number of packets that can be sent on the occupied link is reduced, which is equivalent to the increased channel erasure probability of the link.

The actual PU behavior does not change according to the spectrum occupied by each link but generally changes according to the serial number of the spectrum. For example, in this slot, the PU occupies the spectrum  $m$ , and the next slot occupies the spectrum  $m + 1$ . However, after the number of spectra occupied by each node in the spectrum access scheme is obtained, the sequence of the occupied spectrum can be fixed for each node. For example, when each node is allocated 16 spectra, it can be set that node 1 will occupy spectra units 1–16 and node 2 will occupy spectra units 17–32, and so on. Node 6 will occupy spectra units 1–16. Therefore, we can perform the above approximation and model the behavior of the PUs using the Markov process as follows.

We simulate the scheme based on Q-learning. In the case where each node does not know the PU behavior and the probability of each link channel erasure, through the method of reinforcement learning, each node updates the Q-table and uses the observation of the environment to choose its own spectrum access in this slot. As a comparison, we implement the method in traditional BATS<sup>[90]</sup> as a baseline. Since there is a maximum of 5 nodes in a two-hop range in a line network, each node is allocated  $80/5 = 16$  spectra. In addition, we compare it with the performance of an optimal solution obtained by solving optimization problem with all the information of channel erasure probability and PU activity.

From a comparison of the average results of 100 independent experiments with different erasure probabilities in Fig. 10, we can see that, consistent with the results of theoretical analysis, the larger the average erasure probability, the smaller the average rank of the target node. For different mean values and variances of channel erasure probabilities, when the variance is

larger, the performance gap between the baseline and the optimal solution generally increases. However, when the probability of erasure becomes greater, the average rank value obtained by the optimal algorithm is also lower. Therefore, the gap between the fixed access baseline and the optimal performance will not continue to increase.

In addition, it can be seen from the simulation results that the proposed algorithm based on Q-learning in the first dozens of slots may select an action with poor performance due to the state-action space exploration, so the average rank value of the target node is low, but after the initial stage of learning, the Q-learning algorithm can quickly achieve better performance than the baseline, and as the learning process advances, the performance of the algorithm improves until it reaches convergence after approximately 200 slots. The converged performance is close to the performance of the optimal spectrum access scheme obtained by solving the optimization problem when the probability of erasure of each link is known.

In Fig. 11, we show the rank distribution of each

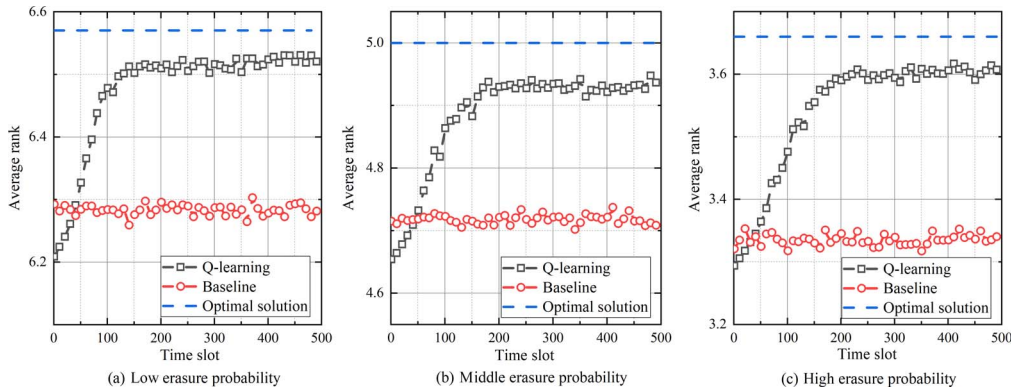


Fig. 10 Average rank at the destination node.

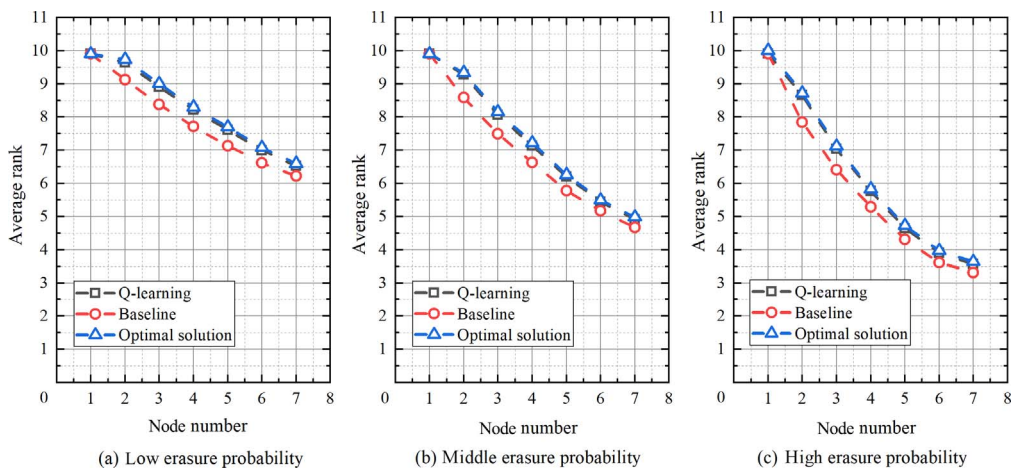


Fig. 11 Average rank at the relay node after the algorithm converged.

relay node and target node when using the Q-learning algorithm and the baseline algorithm. It can be seen that the average rank of the Q-learning-based algorithm decreases smoothly with the number of hops after convergence because the number of spectra allocated to each node, that is, the number of packets sent, will find a value suitable for the link's erasure probability with the learning process. However, the fixed access scheme will significantly reduce the average rank at the link with the higher probability of erasure. Therefore, the average rank declines faster than the Q-learning algorithm after averaging the results of multiple experiments.

As shown in Fig. 12, under the condition of middle erasure probability, the performance of the proposed algorithm with the different number of nodes along the path is compared. The simulation is performed in single-path unicast scenarios with six, eight, and ten hops, respectively. The simulation results show that as the number of link hops increases, the convergence speed of the algorithm decreases, but it can still achieve higher performance than traditional BATS after a few slots. In addition, after the algorithm converges, the average rank of nodes at the same hop little decreases with the increase of the total hop number in the link, which also verifies the scalability of the proposed algorithm.

### 8 Conclusion

In addition to introducing several key technologies of cognitive spectrum collaboration with survey of their development, this paper proposes a solution for the joint optimization of dynamic spectrum access and coding in cognitive spectrum collaboration scenarios.

The simulation results verify the effectiveness of the proposed algorithm.

Future research directions include the following points.

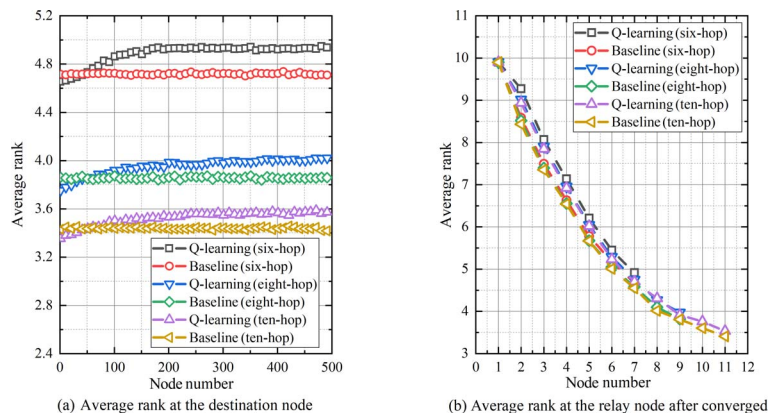
In practice, the network cannot often be simply divided into a combination of unicast networks. It can combine the concepts of BATS codes<sup>[90]</sup> and FUN codes<sup>[100]</sup> and conclusion in scenarios such as overhearing<sup>[96]</sup> to generalize relevant conclusions in more general networks.

In more general networks, due to the complexity of the network structure and the increase in network nodes, related tools, such as deep learning, can be used to reduce the parameters required for reinforcement learning, improve the efficiency of exploration, and accelerate convergence.

The PU behavior set in this article follows a simple Markov process, so the Q-learning promoted from Markov Decision Process (MDP) can achieve superior learning performance. For a more complicated type of PU behavior, a more suitable implementation of reinforcement learning can be chosen.

In addition, the above joint optimization problem of spectrum access and coding can be further jointly optimized with cooperative spectrum sensing problems.

In addition, there may be a confrontation in the cognitive spectrum collaboration scenario. Coding methods, such as BATS codes, have anti-interference ability. How to obtain the optimal coding structure and packet transmitting scheme in the confrontation scenario by combining the design of dynamic spectrum access is a direction of future research.



**Fig. 12** Performance of the proposed algorithm with different numbers of nodes in the path.

## Appendix

### A Proof of existence of the conflict-free access scheme

**Lemma 1** As long as the sum of the number of spectra occupied by neighboring nodes within two hops is less than or equal to the number of available spectra  $M$ , a conflict-free access scheme can be found to satisfy  $t_k$  at each hop in a line network. This conclusion is not necessarily true in networks that are not lines.

**Proof** In a line network, the neighbors within two hops of node  $k$  are nodes  $k - 2, k - 1, k, k + 1, k + 2$ , and the neighbors within two hops of node  $k - 1$  are nodes  $k - 3, k - 2, k - 1, k, k + 1$ . When there is a conflict-free access scheme in the neighbors within two hops of node  $k - 1$ , node  $k + 2$  can directly use the spectra used by node  $k - 3$  and find a conflict-free access scheme in the neighbors within two hops of node  $k$ . However, in a network that is not a line, node  $k - 3$  may be neighbors within two hops of node  $k + 2$ . They cannot share the same spectra, so it cannot be guaranteed that they can find the corresponding conflict-free access scheme. ■

### B Proof of invariance of the optimal strategy

**Lemma 2** When the channel erasure probability remains stable and the max-min criterion is used to ensure fairness without distinguishing the importance of different batches, then the optimal strategy should be fixed in each slot.

**Proof** Assume that an access scheme is an optimal strategy. If this access scheme is adjusted in slot  $i + k$ , when batch  $i$  is transmitted to node  $k$ , node  $k$  will be given more opportunities to send packets, which will cause the number of packet sendings of batch  $i + 1$  in node  $k - 1$  to be reduced, causing the rank distribution of other batches to decrease. If the average rank of other batches in the changed solution does not decrease, the changed solution is a better solution than the original optimal solution, which is contradictory. Hence, the optimal strategy should be fixed in each slot. ■

### Acknowledgment

This work was supported by the National Natural

Science Foundation of China (No. 61790553), Shenzhen Science and Technology Plan Projects (No. JCYJ20180306170614484), and Shanghai Municipal Science and Technology Major Project (No. 2018SHZDZX04).

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