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Genetic Algorithm-based Hybrid Spectrum Handoff Strategy in Cognitive Radio-based Internet of Things

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Abstract In Cognitive radio-based Internet of Things (CR-IoT) systems, the return of the primary user (PU) causes the secondary user (SU) that is communicating to face the spectrum handoff problem. In the process of spectrum handoff, the user terminal can't get the idle channels in time because of the unknown channel usage state. To solve this problem, a hybrid spectrum handoff algorithm based on the channel idle probability is proposed. The algorithm considers the regularity of PU activities in space and time, defines the idle probability of channels from the perspective of week attributes and time periods, obtains the optimal time period length using genetic algorithm, generates a channel idle probability table, and provides the target channel sequence for SUs in combination with the proposed channel ordering scheme. Simulation results show that the hybrid spectrum switching algorithm based on the channel idle probability can reduce the energy consumption of SUs during spectrum switching, reduce the communication interruption rate, enable SUs to find idle channels faster and reduce the number of sensing times.

Keywords Cognitive radio-based Internet of Things · Central cognitive device · Channel idle probability · Hybrid spectrum handoff

1 Introduction

The Internet of Things(IoT) is a ubiquitous technology that communicates with each other by complexly integrating devices (or things) around us to form a closed network of connections to solve real-life problems intelligently [1]. Many IoT devices are mobile, small, and located in decentralized locations [2]. Therefore, wireless networks are considered the most suitable communication mode to connect these devices effectively [3]. Ten-

s of thousands of devices connected through networks constitute the IoT. All physical objects in the IoT can communicate without human intervention, share information, and coordinate decisions [4]. Through the deep integration of physical and digital worlds, IoT revolutionizes the connection and interaction between all objects, and everything will have the ability to sense the environment [5]. With the development of information technology, IoT will penetrate all aspects of the economy, such as intelligent transportation, environmental sensing, smart homes, smart cities, education, industrial monitoring, food traceability, surveillance, and wise collection [6]. According to Intel China in the Future of Intelligent Edge Computing Forum, global IoT devices will reach 100 billion by 2025.

Communication between IoT devices requires spectrum bandwidth, and the growing number of connected objects in the IoT poses multiple challenges, including a scarcity in the spectrum [7]. IoT devices currently use Bluetooth and ZigBee for data transmission in the unlicensed ISM(Industrial Scientific Medical) bands. With the increase of Internet of Things devices, the frequency band in ISM is almost entirely occupied, and the

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transmission distance supported by traditional wireless technologies can reach 100 meters [8]. Therefore, these conventional wireless technologies are unsuitable for IoT applications, such as smart grid, intelligent vehicle transmission, and environmental monitoring, where deployed smart IoT devices need to communicate with remote base stations [9]. The spectrum scarcity problem is also related to spectrum utilization and the technology used [10]. In the traditional spectrum allocation scheme, the licensed spectrum is not fully used. The spectrum utilization is below 3 GHz at roughly 30% and only 0.5% from 3-6 GHz, leaving upwards of 70% of spectrum resources underutilized and spectrum resources severely wasted [11]. The Federal Communications Commission (FCC) proposed cognitive radio technology can effectively address this problem [12]. Cognitive radio technology allows unlicensed SUs to dynamically and opportunistically utilize a portion of the licensed spectrum by adaptively changing their operating parameters (transmit power, carrier frequency, modulation energy, etc.) while providing performance guarantees to the traditional primary user (PU) [13]. A promising solution to the spectrum shortage is the use of cognitive radio technology in the IoT, which gave rise to the Cognitive Radio based Internet of Things (CR-IoT) [14]. By applying cognitive radio technology to the IoT, IoT devices can reuse spectrum and avoid collisions. In addition, with cognitive radio capabilities, IoT devices will have easier access to many networks and services and the system will be scalable [15]. In a cognitive IoT system, IoT devices with cognitive capabilities are called secondary users (SUs). In a cognitive IoT system, when a PU returns or the spectrum quality deteriorates, the SU needs to suspend its ongoing transmission, free up the channel, and identify a target channel to resume its transmission. This process is called spectrum handoff [16].

1.1 Motivation

In a CR-IoT system, the SUs can use the following methods when performing spectrum handoff: proactive, reactive, and hybrid spectrum handoff schemes [17]. Before establishing a data connection, the proactive spectrum handoff scheme predetermined the target channel sequence based on long-term statistics. This approach saves detection and handshaking time at each handoff but requires dealing with obsolescence when the target channel is no longer available. The reactive spectrum handover scheme detects idle channels at the SU unit at the beginning of each handoff procedure [18]. In this method, the time of detection and handshake must be taken into account. In addition, the order and

number of sensing channels must be considered for efficient transmission. Although this scheme can obtain free channels for handoff, it still suffers from handoff delays during spectrum sensing. The hybrid handoff scheme combines the above two handoff schemes (proactive and reactive spectrum handoff schemes) by applying proactive spectrum sensing and reactive handoff actions [19]. In other words, it takes advantage of fast response and accurate target selection in proactive and reactive handoff schemes and can realize fast spectrum handoff with a short waiting time [20].

When the PU returns to the authorized channel, the SU occupying the channel must unconditionally quit immediately to avoid affecting the use of the PU. Only when the PU is free, the authorized channel can be competed by SUs on a "first-come, first-served" basis, and the activity of the PU is the main factor affecting whether the authorized channel is free or not. This paper proposes a hybrid spectrum switching scheme based on channel idle probability from the perspective of statistical analysis of PU activity on the channel, which can provide an effective spectrum selection strategy for SU spectrum handoff.

1.2 Contribution

The contributions made in this paper are as follows:

- (1) PU activity has the characteristics of regularity in space and time. This paper puts forward the idle probability table according to the week attribute of the spectrum handoff moment and the idle probability of each channel in the time period.
- (2) Considering the reason why SUs stop using authorized channels near the moment of spectrum handoff, a target channel sequencing scheme is proposed to enable SUs to detect idle channels faster.
- (3) The genetic algorithm is used to calculate the optimal period length, which makes the obtained channel idle probability table more referential.
- (4) Ordinary SUs can not perform the complex calculation of channel idle probability and large-capacity data storage, so the solution is proposed by using a central cognitive device. The central cognitive device assigns the target channel sequence to the SU to obtain the channel detection ranking with high idle probability and enable it to detect the idle channel as soon as possible.

1.3 Organization

The rest of the paper is organized as follows. In Section 2, we summarize the related work. Section 3 describes

the system model and the proposed channel idle probability algorithm. In Section 4, simulation experiments are performed, and the results are compared and analyzed. Finally, Section 5 draws conclusions.

2 Related work

During spectrum handoff, SU needs to find an idle channel to continue transmission. In the process of finding the inactive channel, it needs to spend its own energy to detect the idle channel until the available channel is obtained or the timeout is interrupted, which will also cause transmission delay. For time-critical transmission requirements, the importance of fast idle channel discovery is even more critical. How to quickly find available channels has been extensively studied by previous authors. [21] proposed an proactive handover scheme based on an artificial neural network to find the best candidate channel. The licensed channel uses the past index of PU activities to train the neural network to obtain a channel list based on the minimum probability of PU occupancy. CR users use the sorted list to obtain the best channel for switching. [22] applies support vector machine (SVM) to CR-IoT network, so that it can learn and adapt to the changing network dynamics, and identify the use of PU spectrum based on the established multi-class (Jx6)d feature set. In [23], the author proposed a predictive spectrum switching scheme for hybrid cognitive radio networks based on deep DQN. In the proposed spectrum switching method, in order to ensure the reliability of spectrum switching, the spectrum switching success rate is introduced into the optimal spectrum resource allocation model, and the closed expression of spectrum switching success rate is obtained based on Poisson distribution. In addition, a transfer learning strategy is adopted to improve the learning process of DQN further. Finally, the priority sequence of available channels of the spectrum switching target is obtained. While meeting the interference constraint between SU and PU, spectrum switching success rate constraint, and SUs performance requirements, the total throughput of HCRNs is maximized. [24] developed an adaptive switching algorithm that allows the SU to detect the arrival of the primary user (through sensing) and adapt to a proactive or reactive switching strategy accordingly. The adaptive switching scheme first allows the SU to decide whether to stay on the current channel and wait or to perform handoff. In the case of switching, the SU intelligently switches between proactive or reactive switching modes depending on the PU arrival rate. The paper, in addition, a PU-first Markov method is proposed to model the interaction between the PU and

the SU for smooth channel access. A new prediction-based spectrum management strategy is proposed in [25]. The strategy fully considers spectrum prediction and user mobility prediction. Combining the prediction information and cooperative sensing, the cognitive radio base station can obtain the sensing information of each SU's future location and thus pre-set high-quality channels for SUs in advance. The authors also propose a new channel selection scheme when multiple channels are available simultaneously. [26] proposed the M/M/1 queuing model for spectrum switching and the shortest queueing selection model for the backup channel after the switching process occurs. The results show that the model has the smallest queueing delay and total system time compared with random selection, which can improve the service quality of SUs. In [27], a new technique based on particle swarm optimization is proposed to minimize the switching delay and maximize the throughput. Reference. [28] proposed a joint optimization problem of spectrum switching delay and link maintenance. A binary-based hybrid SFLA algorithm is proposed to address this problem. The algorithm outperforms the random target channel access scheme. It can obtain a solution with low switching delay and low switching failure probability close to the optimal solution. The spectrum switching scheme using the intrusive weed optimization (IWO) algorithm proposed in [29] under hybrid spectrum switching, thus improving the efficiency of frequency switching in CR networks. To reduce the delay time of SUs, the paper [30] proposes a hybrid preemptive/non-preemptive recovery priority model in which the priority of SUs increases with each interruption of the PU. For the case of a fully busy channel, the paper considers a hybrid spectrum switching combined with random target channel selection. The form derives the closed-form expressions for the average cumulative delay time and extended data delivery time for each SU class is derived in the paper. The analysis table of different spectrum handoff schemes in the related work is shown in Table.1.

3 System Architecture

3.1 System Model

This system uses the central cognitive device, and uses it to allocate the target channel sequence required for spectrum switching to SU. The central cognitive device combines the channel idle probability and the target channel ordering scheme to generate the sequence and send it to the SU for sensing. System operation process: When the SU needs to switch the spectrum, it must send a request to the central cognitive device to

Table 1: Analysis table of different spectrum switching schemes in related work

References	proactive spectrum handoff scheme	reactive spectrum handoff scheme	hybrid spectrum handoff scheme
[21]	✓		
[22]	✓		
[23]	✓		
[24]	✓	✓	
[25]		✓	
[26]		✓	
[27]		✓	
[28]			✓
[29]			✓
[30]			✓
Our proposed scheme			✓

obtain the target channel sequence. After receiving the request, the central cognitive device first determines the week attribute and the detection time period. According to this information, it learns the idle probability corresponding to each channel from the channel idle probability table. At the same time, it refers to the proposed channel sorting scheme to generate the target channel sequence to be detected, and sends the sequence to the SU. After receiving the sequence information, SU detects the channels in the sequence in order. When the channel with the highest ranking is in the occupied state, it sequentially detects the channels slightly lower than its position. It continues this way until the idle channel is seen. When the SU stops using the found idle channel, it reports the channel detection and the reason for stopping using this channel to the central cognitive device. The central cognitive device updates the idle probability of the corresponding channel and records the reasons for channel deactivation. In this way, the obtained data are constantly updated, resulting in a channel idle probability with more excellent predictive reference. The system architecture is shown in Fig.1.

Fig. 1: System Model

3.2 proposed channel idle probability algorithm

3.2.1 Channel idle probability and idle probability table

The channel idle probability is the probability that the channel is inactive when the SU is performing channel detection. Assuming a total of $(N_{detect})_{i,(k,t)}$ detections of channel ch_i during week attribute k , time slot t (denoted as (k, t)), of which $(N_{free})_{i,(k,t)}$ channels are idle, the idle probability $(P_{free})_{i,(k,t)}$ of channel ch_i at (k, t) is expressed as

$$(P_{free})_{i,(k,t)} = \frac{(N_{free})_{i,(k,t)}}{(N_{detect})_{i,(k,t)}} \quad (1)$$

The value range of $(P_{free})_{i,(k,t)}$ is between 0 and 1. The larger the value of $(P_{free})_{i,(k,t)}$, the greater the idle probability including the channel ch_i .

3.2.2 Optimal length of time period obtained by genetic Algorithm

By counting the usage of all channels in the fixed environment, the idle state attributes of channels several times a week can be obtained. To generate the initial channel idle probability table, it is also necessary to determine the optimal slot length of the division time. According to the time slot length, a day is divided in-

to multiple time slots, and the idle probability of each channel of the time slot is obtained according to the formula of channel idle probability. If the slot length is too large or too small, the performance of the proposed spectrum switching algorithm will be degraded. The selection of the time slot length affects the accuracy of the channel idle probability table. To solve this problem, a scheme based on a genetic algorithm to obtain the optimal time slot length is proposed in this paper.

A genetic algorithm (GA) is an optimization algorithm inspired by natural biological evolution. It finds the most suitable gene for the natural environment by selecting, crossing, and mutating the genes in a population and is widely used to search for the optimal solutions to various scientific and engineering problems.

In the scheme of obtaining the best time slot length based on a genetic algorithm, the genetic algorithm tries to find the best time slot length for time-division, so that SU can get the idle channel fastest by querying the channel idle probability table. A genetic algorithm obtains the best value through a series of iterative operations.

The proposed scheme for obtaining that optimal period length base on genetic algorithm consists of the following parts:

Step1: Initial population

Initially, the initial population is set to consist of N individuals, and the genetic algorithm initializes the population by randomly generating N chromosomes, while binary coding them and transforming them into the space that the genetic algorithm can handle.

Step2: Population fitness

The fitness function of population is a key factor to evaluate the fitness of population. Combined with this paper, the set population fitness function is considered in combination with the number of detections required by SU to detect the target channel sequence to obtain the idle channel and the length of the time period.

The fitness function is:

$$Fit(Duration) = \sum_{j=1}^n Num_test_{j,(k,t)}(Duration) \quad (2)$$

where n is the total number of experiments and $Duration$ is the time period length. $Num_test_{j,(k,t)}$ is the number of detection times when SU found the free channel in the j experiment in (k, t) .

Step3: Selection, crossover and variation

The fitness value of each individual in the initial population is first obtained, and the roulette wheel method is used to determine the proportion of the roulette wheel occupied by each individual based on the fitness value, and then the chromosomes that can be inherited to the

next generation are selected from the initial population. The crossover probability is set, and when the randomly generated probability value is greater than the crossover probability, the selected chromosomes are crossed, and the selection of the crossover rate determines the frequency of the crossover. When the crossover rate is larger, the generations can be crossed adequately, but the crossover does not necessarily produce offspring with high fitness, which can lead to a greater possibility of destruction of the selected good genes in the population, thus producing a larger generation gap, which will make the search tend to be randomized; when the crossover rate is set lower, the generation gap produced will be smaller, which will make more of the selected current good individuals replicate directly to the next generation, and the genetic The crossover rate selected in this experiment is 0.6. Similarly, the selected mutation rate also affects whether chromosomal gene mutation is performed, and the mutation operation will be triggered when the probability of random generation is greater than the mutation rate, and the rate selected in this experiment is 0.008.

Step4: Stop conditions

The iteration is stopped when the children generated by the above steps have the required fitness value or when the maximum number of iterations is reached, otherwise the above steps are repeated.

3.2.3 Target channel sorting scheme

The channels are sorted according to the corresponding probabilities in the idle probability table from largest to smallest to generate the initial target channel sequence. the SU uses the idle channel for transmission encounters two situations: (1) the SU uses the idle channel for transmission in the process, the PU returns, and the SU is forced to stop transmission and perform spectrum switching. (2) The SU completes the data transmission using the idle channel without any problem. After the transmission is completed, the SU stops channel occupation. To reduce the time and energy consumed by the SU to detect the idle channel, this paper makes the following improvements to the initial target channel sequencing scheme: for case (1), the SU shall actively report the interruption of the used channel to the central cognitive device. When the central cognitive device needs to generate the target channel sequence within a short period of time, it is always placed at the bottom of the target channel sequence to be generated, regardless of the idle probability of this channel at that moment. For case (2), the SU reports normal usage information to the central cognitive device. In a short time, if the central cognitive device needs to generate

a target sequence, it is always placed at the top of the target channel sequence to be generated, regardless of the value of the idle probability of this channel.

3.2.4 Channel idle probability table update

Through the above method, the channel initial idle probability of each channel in different time periods in each week attribute is obtained. The probability is updated every time of subsequent detection. It is updated to get the channel idle probability with a more excellent reference.

Every time the channel ch_i is detected, the number of channel detections in the corresponding (k, t) is increased by 1, that is:

$$(N_{detect})_{i,(k,t)} = (N_{detect})_{i,(k,t)} + 1 \quad (3)$$

When the detected channel ch_i is idle in (k, t) , the channel idle probability of the corresponding period is updated:

$$(N_{free})_{i,(k,t)} = (N_{free})_{i,(k,t)} + 1 \quad (4)$$

$$(P_{free})_{i,(k,t)} = \frac{(N_{free})_{i,(k,t)}}{(N_{detect})_{i,(k,t)}} \quad (5)$$

Similarly, when the detected channel ch_i is occupied, Channel idle probability in (k, t) update :

$$(P_{free})_{i,(k,t)} = \frac{(N_{free})_{i,(k,t)}}{(N_{detect})_{i,(k,t)}} \quad (6)$$

where the value of $(N_{idle})_{i,(k,t)}$ remains unchanged.

3.3 Algorithm Complexity Analysis

The complexity of the proposed hybrid spectrum handoff algorithm based on the channel idle probability depends mainly on the genetic algorithm and the fitness function. The complexity of the genetic algorithm is mainly related to the comparison between the individuals in the population and the rest of the individuals to obtain the optimal solution, and the complexity is $O(N)$. The complexity of the fitness function is measured to be independent of the length of the selected time period, and only related to the total number of channels in the system, and its complexity is $O(M^2)$. The complexity of the proposed algorithm is $O(N \cdot M^2)$.

3.4 Example of hybrid spectrum handoff algorithm based on channel idle probability

It is assumed that there are 5 authorized channels in a fixed environment and an initial channel idle probability table has been obtained. As shown in Fig.3, an example is given to illustrate the four spectrum handoff processes for SUs in the hybrid spectrum handoff algorithm based on channel idle probability. As shown in Fig. 2.

(1) At the beginning, the SU_1 transmits data on the target channel Ch1, and the PU returns in the process, resulting in the first interruption. The SU_1 reports the interruption of transmission on the authorized channel Ch1 to the central cognitive device, and the central cognitive device inquires the channel idle probability corresponding to the week attribute and time period in the channel idle probability table. At this time, the channels are in the order of Ch2, Ch5, Ch1, Ch4 and Ch3 according to the idle probability from large to small. Ch1 is the channel returned by PU at this time, which causes transmission interruption, so the target channel sequence (Ch2, Ch5, Ch4, Ch3, Ch1) for spectrum handoff is obtained. The SU_1 finds the first channel Ch2 from the sequence, and after detecting that Ch2 is idle at the moment, SU_1 accesses the channel Ch2.

(2) In the second interruption, SU_1 reports the interruption of transmission and obtains that the channels are sorted by idle probability: Ch5, Ch2, Ch1, Ch3, Ch4 by referring to the channel idle probability table at this moment. The target channel sequence is (Ch5, Ch4, Ch1, Ch3, Ch2), and SU_1 finds the target channel as Ch5 from the sequence, but it is detected that the channel Ch5 is occupied at the moment. Therefore, continues to select the channel Ch4 from the target channel sequence, and it is detected that the channel Ch4 is idle at the moment, and SU_1 accesses the channel Ch4. And update the idle probabilities of channels Ch5 and Ch4 at this moment.

(3) In the third interruption and same cluster, a short time before spectrum handoff occurs in SU_1 , SU_1 normally uses up channel Ch3 and releases it, and at this moment, the channels are sorted as Ch5, Ch3, Ch2, Ch4 and Ch1 according to idle probability. Combined with SU_2 , the target channel sequence of SU_1 at this time is (Ch3, Ch5, Ch2, Ch1, Ch4) because channel Ch3 is normally used up. The SU_1 obtains the primary idle detection channel Ch3 from the target channel sequence, and after detecting that Ch3 is idle at the moment, SU_1 accesses Ch3 to continue transmission and updates the idle probability of Ch3 in the channel idle probability table.

(4) Not long after SU_3 in the same cluster stopped us-

Fig. 2: Example of hybrid spectrum handoff algorithm based on the probability theory of channel idleness

Table 2: Parameter Setting

Parameter	Value
Total number of channels	5
Total number of SUs	10
Total number of tasks	50~70
Task duration (s)	80
Energy consumed by detecting SU primary channel	0.05J
Energy consumed by SU to transmit 1 second of data	0.1J

ing channel Ch5 because PU returned, SU_1 was interrupted for the fourth time. At this moment, the order of channel idle probability is Ch5, Ch2, Ch4, Ch3 and Ch1. Because SU_3 stops using channel Ch5 due to PU return, the target channel sequence of SU_1 at this time is (Ch2, Ch4, Ch3, Ch1, Ch5). The SU_1 obtains the primary channel Ch2 to be idle from the target channel sequence. After detecting that Ch2 is idle at the moment, accesses Ch2 to continue transmission and updates the idle probability of Ch2 in the channel idle probability table.

4 Performance Analysis

In this section, we use the Matlab experimental platform for communication simulation. The performance of the proposed spectrum switching scheme is evaluated by comparing it with proactive and reactive spectrum switching schemes and Scheme of Sukhen Shil et al in terms of transmission performance.

4.1 Simulation parameter setting

In the simulation, we consider the entire spectrum is uniformly divided into 5 sub-channels for data communication. The common control channel is used for coordination between the central cognitive device and SUs. Note that the common control channel for coordination between the central cognitive device and the SUs is separate from the data channel. There are 10 SUs

in the network. Every authorized channel has a 20% chance of being occupied by PU. To evaluate the performance of the hybrid spectrum switching algorithm based on channel idle probability in a network with different task volumes, we vary the total task volume that requires SUs to send in the system from 50 to 70. We make the sending time of each task equal to 80 seconds, and the sending time of the task is uncertain. In the experiments, the energy consumed by the SU for each idle detection of the channel and for each second of data transmission is assumed to be fixed values, denoted as E_{test} and E_{pass} , respectively.

The energy consumed E_{sum_test} by detecting the idle channel of SU for E_{test} times is:

$$E_{sum_test} = N_{test} \times E_{test} \quad (7)$$

SU transmission N_{pass} time, the energy consumed E_{sum_pass} is:

$$E_{sum_pass} = N_{pass} \times E_{pass} \quad (8)$$

4.2 Performance comparison of three different spectrum switching modes

Compare the performance of SUs in performing spectrum switching with three spectrum switching methods, i.e., proactive, reactive, and hybrid spectrum switching based on channel idle probability, respectively.

Fig.3 shows that when the number of tasks to be sent in the whole experiment increases from 50 to 70, the performance comparison of the proactive, reactive and proposed spectrum switching methods based on the channel idle probability when SU performs spectrum switching, respectively.

From Fig.3 (a) and (b), it can be seen that only when the total number of tasks in the system is 62, the energy consumed by the SU to complete the transmission task by using the proposed spectrum switching methods is greater than that consumed by the reactive spectrum switching. In other cases, the energy consumption and time required to complete the transmission task by using the proposed spectrum switching method for SU spectrum switching are less than those by using the other two techniques.

In the whole communication process, the total number of sensing times for each SU to obtain idle channels during spectrum switching is shown in Fig.3(c). It can be seen from the figure that under the same channel conditions, the total number of sensing times required by SU to adopt the proposed hybrid spectrum switching is less, which has been fluctuating around 10

Fig. 3: Performance comparison of three different spectrum handoff schemes

times. The maximum sensing times of proactive spectrum switching are always more than 70 times. Because the proposed probability-based hybrid spectrum switching method selects the channel with higher idle probability for detection according to the statistical characteristics of each channel occupied by PU at each moment. The detection times of obtaining inactive channels are less, and the idle channels can be found quickly.

Fig.3(d) shows the number of SU interrupts. When the PU is returned in the grant channel, the transmitting SU must quit immediately and find an idle channel to continue the transmission. The time of waiting for the free channel of SU is limited. If SU has not found the free channel for transmission within the specified time, then SU terminates the transmission, that is, the communication is interrupted. It can be seen from Fig.3(d) that the interruption times of hybrid spectrum switching based on channel idle probability in SU transmission are always 0 times, which is far less than the communication interruption times caused by proactive spectrum switching in SU. Because the proposed hybrid spectrum switching can find the idle channel more quickly, so as to continue the transmission and avoid the communication interruption caused by too long waiting time.

Under the condition of the same amount of tasks in the system, the longest time from the beginning

of sending data to the completion of sending data for each SU in the system is compared, including the delay time of spectrum switching. The comparison is shown in Fig.3(e) below. It can be seen from the figure that the longest transmission time required by proactive spectrum switching and hybrid spectrum switching in SU is not much different, while the longest transmission time required by reactive spectrum switching in SU is longer. Because when the total number of channels in the transmission environment is small, SU uses reactive spectrum switching to detect channels randomly. It is challenging to obtain idle channels immediately, so SU will take a long time for SU to transmit the same amount of data.

4.3 Comparative experiment

The spectrum switching algorithm based on channel idle probability proposed in this paper is compared with the spectrum switching algorithm proposed by Sukhen Shil el al in [31]. The experimental environment is the same as that in 4.2. When the total number of tasks increases from 50 to 70 in the experimental environment, the performance indexes of the two spectrum switching modes are compared. The experimental results are shown in the figure below.

Fig. 4: Performance comparison of Comparative experiments

From Fig.4 (a), (b), (c), (d), it can be seen that the hybrid spectrum switching algorithm based on channel idle probability has an advantage over the spectrum switching algorithm proposed by Sukhen Shil et al. in terms of the time required to complete the system task transmission, the energy required for transmission, the maximum number of spectrum switching large senses, the total number of spectrum switching senses and the number of communication interruptions when under the same conditions. It can be seen from Fig.4(e) that in terms of SU maximum transmission time, the method proposed by Sukhen Shil et al. is better.

5 Conclusion

In this paper, a hybrid spectrum handoff algorithm based on channel idle probability is proposed to help devices in CR-IoT find idle channels to continue transmission. The target channel sequence is generated by using the channel idle probability table and the proposed target channel sorting scheme, so as to reduce the waiting time of spectrum handoff of CR-IoT devices and find idle channels faster. Simulation studies show that the hybrid spectrum handoff algorithm based on channel idle probability can obviously improve other performances such as total transmission time consump-

tion, total transmission energy consumption, and Maximum number of sensing times for spectrum handoff.

In the future work, we will study how to make the CR-IoT devices get idle channels to continue transmission more quickly when several devices need to switch spectrum in a short time. In addition, the proposed hybrid spectrum handoff algorithm will be optimized by combining the Markov model to make the target channel sequence more effective.

Declarations

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Data Availability Data can be shared and is available on request. Data can be requested by sending an email to the main author.

Conflict of interest The authors declare that they

have no conflict of interest.

Authors' contributions Liu Miao conceived and designed the study. He Qing designed the study and performed experiments. Liu Miao and He Qing wrote the paper. Zhuo-Miao Huo, Xu Di and Zhen-xing Sun edited the manuscript.

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