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Channel Status Learning for Cooperative Spectrum Sensing in Energy-Restricted Cognitive Radio Networks

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ABSTRACT A cognitive radio (CR) is a promising technology to solve the emerging spectrum crisis, especially for applications where thousands of wireless sensor nodes are deployed. Since continuous spectrum sensing will greatly reduce the lifetime of a network composed of energy-restricted CR nodes, an accurate method for predicting spectrum occupancy is necessary to improve energy efficiency. This paper proposes a hidden Markov model (HMM)-based cooperative spectrum sensing (CSS) that predicts the status of a network environment. The traditional prediction algorithms for cooperative spectrum sensing assume that all CR nodes have the same network environment. However, the channel availability of various CR nodes can be quite different, and thus the traditional algorithms will lead to low prediction accuracy in a complex radio environment. The proposed methods learn the historical spectrum sensing results and help the network to make an energy-efficient spectrum sensing decision. More specifically, the hidden state of HMM is set to different areas, where primary users (PUs) perform different activities. A Baum-Welch (BW) algorithm is employed to estimate the parameters of the HMM based on the past spectrum sensing results, and then the parameters are fed to a forward algorithm for the predicting of PUs' activity. Based on the prediction, secondary users (SUs) are classified into either "interfered by PU" or "not interfered by PU." The nodes selected as "interfered by PU" will not perform spectrum sensing to reduce unnecessary energy consumption. The performance of the proposed method is evaluated using the simulations under different traffic conditions. The simulation results show that, compared with the conventional HMM-based methods, the effectiveness of the proposed algorithm in energy efficiency and spectrum utilization improved by about 13% and 15%, respectively.

INDEX TERMS Cognitive radio, hidden Markov model, spectrum sensing, energy efficiency.

I. INTRODUCTION

Wireless communication requirement in IoT services is rapidly growing, and the ISM spectrum based networks (e.g., Wireless Sensor Networks, Wireless Body Area Networks and Vehicle-to-Vehicle Networks, etc.) cannot provide the expected communication reliability and throughput due to the overcrowded spectrum [1], [2]. Therefore, cognitive Radio (CR) has been proposed as a promising technology to solve the emerging spectrum crisis. In order to efficiently utilize the underutilized licensed spectrum,[1] Secondary Users (SUs) need to adapt Dynamic Spectrum

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[1](Studies show that spectrum occupancy seems to peak at about 14%, except under emergency conditions, where occupancy can reach 100% for brief periods of time [3])

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Allocation (DSA) to maximize the utilization of idle licensed spectrum in an opportunistic manner [4]. When an SU wants to utilize a licensed channel, it will observe and measure the state of the spectral occupancy (i.e., idle/busy) by performing *spectrum sensing* [5]–[7]. Due to multi-path fading effect, the cooperative spectrum sensing (CSS) technology is employed. The main idea of CSS is for SUs to share their spectrum sensing information to determine the status of a licensed channel more accurately than using individual decisions.

However, frequent spectrum sensing will reduce the network lifetime of wireless communication devices in IoT, which are typically battery powered. Therefore, developing an energy-efficient spectrum sensing method is crucial. To overcome this problem, Qu *et al.* proposed a method to decrease the energy consumption by selecting only few SUs with high detection accuracy and then distribute the sensing results to the neighboring SUs [8]. This method can be further enhanced by applying machine learning methods. Bhowmick *et al.* have proposed a technique that utilizes historic data, where SUs predict the future state of a channel and then either sense the channels that are marked as idle or harvest energy from the channels that are marked as busy [9]. Eltom *et al.* proposed a Hidden Markov Model (HMM) based spectrum prediction algorithm to accurately predict the spectrum state of the next time slot [10].

However, the aforementioned schemes assume all SUs operate under the same network environment, i.e., all the SUs cannot access the licensed channel if the *Primary User* (PU) is active. In certain CR networks, when a PU is active, it will prevent SUs located around the PU to access the licensed channel, while other SUs who are far from the PU can utilize the licensed channel [11].

To solve the problem, this paper proposes an *HMM-based Cooperative Spectrum Sensing* (CSS) method, by classifying SUs as either 'Interfered by PU' (IP) or 'Not Interfered by PU' (NIP) set, all the SUs can be managed to either stop (even though SUs belonging to the NIP set can access the channels) or perform spectrum sensing (even though SUs belonging to the IP set can actually stop spectrum sensing to save energy). Thus, efficiency of these schemes decrease in terms of both energy consumption and spectrum utilization. Meanwhile, the mobility of the PU changes the IP and NIP sets quickly, thus the proposed scheme considers this dynamic process. The main contributions of the proposed HMM-based CSS method can be summarized as follows:

- In order to track the activity of the PU in an energy-restricted CR network, an *Interference Zone* (IZ) is defined to denote the area in which a PU exists. An energy-restricted CR network can be divided into several IZs so that the PU's activity within an IZ will be tracked by labeling SUs that are interfered by the PU.
- In order to predict the PU's existence, an HMM-based prediction algorithm is applied. Spectrum sensing results from SUs in the various IZs are combined at the Fusion Center (FC) using a fusion rule for modeling a specific HMM. Then, a forward algorithm is employed to predict the existence of a PU in the next time slot. Based on the prediction, the SUs that are interfered by PUs will be prevented from spectrum sensing to save energy.
- To reduce unnecessary energy consumption during spectrum sensing, a prediction-based spectrum sensing node selection algorithm is proposed. The algorithm selects SUs that have both high remaining energy and detection probability from the NIP set according to prediction for cooperative spectrum sensing. Based on the majority-rule, the final decision for cooperative spectrum sensing is made at the FC and then shared with other SUs.

The rest of the paper is organized as follows. The related work is discussed in Section II. Section III describes the system model. The proposed HMM-based Cooperative Spectrum Sensing scheme is presented in Section III. Section IV provides simulation results of the proposed scheme and Section V concludes the paper.

II. RELATED WORK

The main idea of cooperative spectrum sensing is to improve the spectrum sensing performance by exploiting the spatial diversity in the observations of SUs. SUs through the cooperation can share their spectrum sensing information, and thus determine the status of the licensed channel more accurately than the individual decisions.

Monemian *et al.* proposed a cooperative method for detecting spectrum sensing SUs, which groups SUs into several sensing clusters based on local and global detection probabilities [12]. The SUs that have lower detection probabilities can be grouped with the SUs that have higher detection probabilities as long as the global detection accuracy is satisfied. The optimal solution is obtained by choosing the group that leads to the minimum average energy consumption (including energy consumed for spectrum sensing and transmission), and performing spectrum sensing and sharing the information with other SUs until all the live clusters can no longer meet the detection accuracy. Ergul and Akan proposed a two-stage sensing method [13]. The first stage involves a fast and coarse sensing to find the channels that are more likely to be available, but the results are inaccurate. In the second stage, a more accurate fine sensing scheme is used for the final decision.

Ren *et al.* proposed a method to improve the energy efficiency by choosing the minimum number of SUs for spectrum sensing [14]. The energy efficiency of collaborative spectrum sensing can be further improved by adaptively isolating the SUs from spectrum sensing. In order to guarantee energy efficiency and sensing accuracy in Ad-hoc Cognitive Radio Networks, Usman *et al.* proposed a three-stage method. In the first stage, each SU starts as a cluster head and then grouped with neighbor SUs into a cluster. A group of SUs that covers an area with minimum overlap are clustered into a subset in the second stage. In the last stage, only one subset of the cluster is selected for spectrum sensing while the rest of the subsets in the cluster are put into sleep mode.

Nguyen and Shin proposed a prediction-and-sensing-based spectrum sharing model for cognitive radio networks [15]. The time slot structure consists of two phases: the prediction and spectrum sensing phase and the data transmission phase. In the first phase, SUs and a secondary Base Station (BS) independently perform predictions for the availability of local licensed spectrum. A fusion center combines the prediction results from both SUs and the secondary BS, and then makes a decision about the licensed spectrum state. Finally, only the BS performs spectrum sensing based on the prediction results and shares the sensing results with SUs. Xing *et al.* modeled the spectrum sensing process as a Non-Stationary HMM (NSHMM), where the channel state transition probability is a function of the time interval [16]. The parameters for the model include expected duration of the channel states and the spectrum sensing accuracy. These parameters are estimated via Bayesian inference, and then used to evaluate the channel quality based on the prediction results. Finally, SUs select the channel that is expected to remain idle for a long time to sense and access spectrums. Yin *et al.* proposed the channel availability vector to characterize the state information of licensed channels [17]. The sensing time can be decreased by figuring out the best channel to sense.

In recent years, the application of artificial intelligence has it made possible to combine machine learning and the CR technology, and a large number of machine learning algorithms have been applied to the study of energy efficient spectrum sensing [18]–[21]. For example, basic HMM-based prediction methods were proposed to predict the next state of channels in [22], [23]. This is achieved by exploiting historic spectrum sensing outputs and having SUs sense only the channels that are predicted to be unoccupied rather than all the channels. Another HMM-based predictor was proposed in [24], but it only deals with deterministic traffic scenarios and thus it is not applicable in a real environment. Unlike most of the existing work where predictions on whether or not the next slot is available for SU transmission, Saad *et al.* presented a HMM-based spectrum prediction that accurately predicts the spectrum occupancy for several time slots in the future [25].

Based on analyzing the features of the existing machine learning based spectrum sensing schemes discussed above, it is clear that none of these considered the challenges of spatiotemporal interference characteristics between SUs and PUs in energy-restricted CR networks. In these schemes, if most of the SUs are predicted to not interfere with a PU, the FC will manage all the SUs to perform spectrum sensing. In fact, some SUs that will interfere with a PU can stop spectrum sensing during next time slot to save energy. Thus, the energy efficiency of the above schemes is actually reduced. Also, if most of the SUs are predicted to interfere with a PU, all the SUs will be managed not to perform spectrum sensing even though some SUs will not interfere with the PU. Thus, the spectrum utilization is decreased. Therefore, the proposed HMM-based CSS considers the two situations and thereby optimizes both energy efficiency and spectrum utilization.

III. SYSTEM MODEL

This section describes the Cooperative Spectrum Sensing model and the background information on the conventional HMM-based modeling method. Then, the details of the proposed modeling method using HMM for TDMA-based networks is presented.

A. COOPERATIVE SPECTRUM SENSING MODEL

This paper considers a cooperative cognitive radio network consisting of k SUs, m PUs, and one Fusion Center (FC). The FC is an information sharing, data storage, and decision making center with unrestricted energy. The network operates in a TDMA manner, where at the beginning of each time slot, SUs detect the status of a channel (i.e., idle/busy) via energy detection technology with a predefined threshold [26]. The spectrum sensing can be formulated as a binary hypothesis testing, where hypothesis H_0 and H_1 indicate that PU is absent and present, respectively. The received signal at an SU, $y(n)$, in the channel being sensed can be expressed as [9]:

$$y(n) = \begin{cases} g(n) & H_0 \\ \alpha s(n) + g(n) & H_1 \end{cases} \tag{1}$$

where $g(n)$ is the additive white Gaussian noise with mean zero and variance σ_w^2, α is the channel gain, and $s(n)$ is the sample of PU's signal. Based on this, the channel state is determined as follows [23]:

$$\begin{aligned} H_0 : &\quad \sum\nolimits_{n=0}^{N} |y(n)|^2 < \lambda \\ H_1 : &\quad \sum\nolimits_{n=0}^{N} |y(n)|^2 \geq \lambda \end{aligned} \tag{2}$$

where λ is the predefined threshold and N is the number of samples. After determining the channel status, SUs send the sensing results '0'/'1', which indicates the channel is idle/busy, to the FC. Note that the channel status is assumed to be stable within a time slot. Furthermore, E_T^i and E_r^i are defined as the total energy consumed and the remaining energy, respectively, by SU_i during spectrum sensing at time T. E_T^i is composed of E_S^i and E_t^i, which represent the energy consumed by SU_i to perform spectrum sensing and transmit the result to the FC, respectively. Then, the FC analyzes the sequence of sensing results from SUs to build an HMM for predicting the channel status (idle/busy).

In order to better understand this process, the following two subsections provide backgrounds on the conventional HMM method and the proposed scheme.

B. HIDDEN MARKOV MODEL

The process of spectrum sensing shown in Fig. 1 can be modeled as an HMM to differentiate between two types of events – observed events (i.e., observations) and hidden events (i.e., hidden states). The hidden states are considered to have generated the observations. The observation o_t is

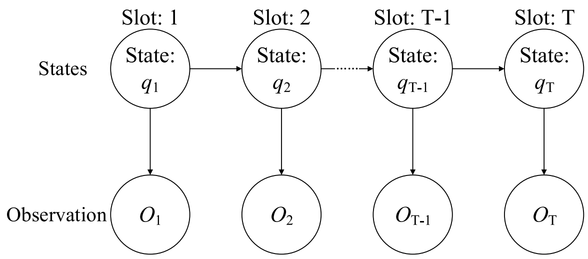

FIGURE 1. The process of spectrum sensing.

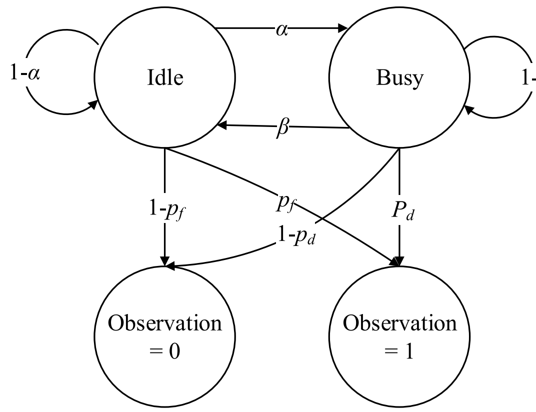

FIGURE 2. The hidden Markov process of cognitive radio network.

obtained from the true state q_t of the channel by SU. A conventional HMM for cognitive radio network has a hidden space $Q = \{q_0 = 0, q_1 = 1\}$, where q_0 and q_1 indicate that the true state of a channel is idle and busy, respectively, and an observation space $O = \{o_0 = 0, o_1 = 1\}$, where o_0 and o_1 indicate that the sensing result of a channel is idle and busy, respectively. However, since spectrum sensing is imperfect, its accuracy (i.e., detection probability p_d and false alarm detection probability p_f) has a significant influence on the observation output as shown in Fig. 2. The detection probability, p_d, indicates when a busy state is detected and the channel is actually busy, while the false alarm probability, p_f, represents when the channel is detected to be busy but it is actually idle. Thus, its *emission* (or *output) probability matrix* B can be defined as

$$B = \begin{bmatrix} b_{00} & b_{01} \\ b_{10} & b_{11} \end{bmatrix}, \tag{3}$$

where b_{ij} indicates that the observation is i when the true channel state is j. Moreover, B can be further calculated as

$$B = \begin{bmatrix} 1 - p_f & 1 - p_d \\ p_f & p_d \end{bmatrix}. \tag{4}$$

Markov state transition chain A can be represented by the following matrix:

$$A = \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix}, \tag{5}$$

where a_{ij} indicates the probability of transitioning from state i to state j. The initial state distribution probability π is defined as

$$\pi = \begin{bmatrix} \pi_0 & \pi_1 \end{bmatrix}, \tag{6}$$

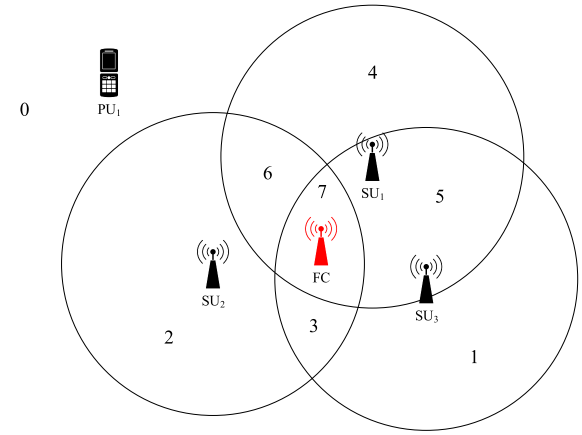

FIGURE 3. Model of an example CRN.

where π_i represents the probability that the initial state of channel is i ($i = \begin{bmatrix} 0 & 1 \end{bmatrix}$).

C. NETWORK MODEL

The assumption of the proposed HMM-based CSS scheme is that a PU's activity will not affect all the SUs, which is different from conventional HMM-based CSS schemes such as those proposed in [14]–[17], [27]. The mobility of PUs is unknown, and thus the location of the PU could be considered as hidden states $Q = \{q_1, q_2, \ldots q_M\}$. These states can be interpreted as IZs as shown in Fig. 3, where the entire network area is subdivided into 8 different IZs, and thus the HMM model has 8 different hidden states. More specifically, for example, when PU$_1$ moves to IZ$_4$, it only interferes with SU$_1$ and other SUs (i.e., SU$_2$ or SU$_3$) can access the PU's channel normally (PU is assumed occupy a single licensed channel)

In order to obtain the observations $O = \{o_1, o_2, \ldots o_n\}$, the proposed scheme schedules SUs to send binary results '0'/'1' to the FC using a common channel after spectrum sensing. The FC then combines the binary results into a sequence X_t. For example, the observation sequence $X_t = \begin{bmatrix} 1 & 0 & 1 \end{bmatrix}$ indicates the sensing result of SU$_1$, SU$_2$, and SU$_3$ is '1', '0', and '1' at time t, respectively.

As shown in Fig. 4, the transition probabilities for the proposed scheme $\left[A = a_{1,1} a_{1,2} \ldots a_{1,M} \ldots a_{M,M}\right]$ are denoted by a_{ij}, which represents the probability that the PU moves from IZ$_i$ to IZ$_j$ and satisfies the condition

$$\sum\nolimits_{j=1}^{M} a_{ij} = 1. \tag{7}$$

Using $[\pi = \pi_1, \pi_2, \ldots, \pi_M]$ to denote the initial distribution, where π_i denotes the probability of being in state i (i.e., IZ$_i$), M is the number of hidden states, and

$$\sum\nolimits_{i=1}^{M} \pi_i = 1 \tag{8}$$

The emission probability of observation O_n in state i is a joint probability. For example, if the PU appears in Fig. 2 in IZ$_1$ at time t and the sequence $X_t = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$ if SU detects correctly, then the binary sequence '100' can be encoded into a decimal number '4' to indicate that the network has observed

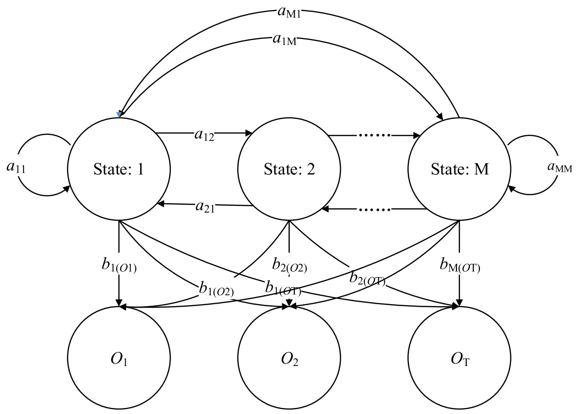

FIGURE 4. The proposed hidden Markov process.

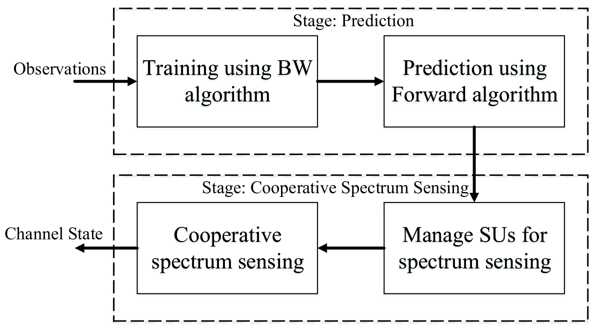

FIGURE 5. Flowchart of the proposed scheme.

the PU in IZ_4. The probabilities of detection and false alarm for SU_i are denoted as p_d^i. The emission probability is

$$\begin{aligned} b_1(X_t = 4) &= P_1(o_t = 1|q_t = 1) \cdot \\ &\quad P_2(o_t = 0|q_t = 0) \cdot P_3(o_t = 0|q_t = 0) \end{aligned} \tag{9}$$

$P_1\,(o_t = 1|q_t = 1)$ equals the detection probability of SU_1, and

$$P_2\,(o_t = 0|q_t = 0) = 1 - p_f^2 \tag{10}$$

$$P_3\,(o_t = 0|q_t = 0) = 1 - p_f^3 \tag{11}$$

Finally, the joint probability can be calculated as

$$b_1(X_t = 4) = p_d^1(1 - p_f^2)(1 - p_f^3). \tag{12}$$

IV. THE PROPOSED SCHEME

The flowchart for the proposed HMM-based Cooperative Spectrum Sensing scheme is shown in Fig. 5. The SUs sense the licensed channels at the beginning of each time slot. After spectrum sensing, each SU determines whether a PU exists according to a predefined threshold and sends its observation to the FC node. Then, the FC encodes all the sensing results into a combination sequence $X_{(t)}$ as mentioned in Section III to build the HMM-based prediction model. The objective of the prediction model is to anticipate the next state based on the past history of observations. Based on the prediction, the SUs can be classified into either the IP or NIP set. The SUs belonging to the IP set will stop spectrum sensing during next time slot. In order to decrease the energy consumption during spectrum sensing, some SUs will be selected to perform cooperative spectrum sensing and their sensing results will be transmitted to the FC. The FC will use a majority-rule to determine the channel status.

A. HMM-BASED PREDICTION

The prediction stage consists of two phases: training and prediction. In the training phase, the parameters $\lambda(A, B, \pi)$ are adjusted based on the result of spectrum sensing using the Baum-Welch algorithm, which can be considered as an expectation-maximization (EM) algorithm. The steps involved in training an HMM is shown in Algorithm 1 and explained below:

Algorithm 1 Baum-Welch Algorithm

Input: Observation sequence $O = \{o_1, o_2, \ldots, o_n\}$, initialization of HMM parameters λ_0
repeat
  Update λ_k with λ_{k-1}
until $P(O|\lambda_k) <= P(O|\lambda_{k-1})$
Output: HMM parameters $\lambda(A, B, \pi)$

Step 1: Initialize the Hidden Markov model's parameters λ_0 and compute the probabilities of observation occurrences for the given parameters.

Step 2: λ_k is estimated based on the observation sequence and the initial parameters of the k^{th} iteration (λ_{k-1}).

Step 3: If $P(O|\lambda_k) > P(O|\lambda_{k-1})$, then repeat Step 2. Otherwise, terminate the procedure and λ_{k-1} becomes the optimal parameters of the model.

After these steps, the following parameters can be obtained: the initial state probabilities $[\pi = \pi_1, \pi_2, \ldots, \pi_M]$, the transition probabilities $\left[A = a_{1,1}a_{1,2}\ldots a_{1,M}\ldots a_{M,M}\right]$, and the optimal emission probabilities $[B = b_1(X_1)\ldots b_M(X_n)]$. These parameters are then used in the prediction phase. Given a combination of observation sequence $[X = X_1, X_2, \ldots, X_n]$, a forward recursion algorithm is employed to calculate the maximum likelihood to predict the future state. A forward variable $\alpha_i(t) = p(X_1, X_2, \ldots X_T, q_T = q_i|\lambda)$ is defined as the probability of having observed the sequence $\{X_1, X_2, \ldots, X_T\}$ while being in state i at time T. The algorithm involves the following three steps:

Step 1: Initialization:

$$\alpha_i(1) = a_{1,i}b_i(X_1), \quad 1 \le i \le M \tag{13}$$

Step 2: Recursion:

$$\alpha_i(T+1) = p(X_1, X_2, \ldots, X_{T+1}, q(T+1) = q_i|\lambda) \tag{14}$$

$$= b_i(X_{T+1})\sum_{j=1}^{M}\alpha_j(T)a_{ji} \tag{15}$$

Step 3: State prediction:

$I_t(t+1)$ denotes the future state i at time $t+1$, which can be calculated by

$$I_t(t+1) = \sum_{X_{T+1}}\left[b_i(X_{T+1})\sum_{j=1}^{M}\alpha_j(T)a_{ji}\right] \tag{16}$$

Finally, the most likely state at time $t+1$ can be obtained using the following equation:

$$I_{t+1} = \operatorname*{argmax}_{i \in \{1,2,\ldots,M\}} I_i(t+1) \tag{17}$$

B. COOPERATIVE SPECTRUM SENSING

After predicting the most likely state for $t+1$, the FC will inform the SUs that will interfere with a PU to stop sensing channels at the beginning of the next time slot to save energy. The SUs that are predicted to not be affected will be grouped into the NIP set. For further enhancing the energy efficiency, some SU nodes will be selected from the NIP set for spectrum sensing. This is achieved as follows:

1) Each SU belonging to the NIP set will evaluate its remaining energy by

$$E_r^{i,t} = E_r^{i,t-1} - E_s^i - E_t^i, \tag{18}$$

where $E_r^{i,t}$ is the remaining energy of SU_i at time t. Thus, SUs in the NIP set can be sorted by remaining energy in decreasing order.

2) n (for $1 \leq n \leq N$, where N is the number of SUs in the NIP set) SUs can be selected from the NIP set to build a cooperative spectrum sensing set, and the global detection probability of a such set can be calculated as:

$$p_{gd} = \prod_{i=1,2,\ldots,N} p_d^i, \tag{19}$$

where p_d^i is the detection probability of SU_i.

3) The cooperative spectrum sensing set can be selected by:

$$\operatorname*{argmax}_{i=1,2,\ldots,N} \sum E_r^{i,t}, \quad s.t.\ (p_{gd} \geq \eta), \tag{20}$$

where η is the predefined threshold.

4) Finally, SUs in the selected cooperative spectrum sensing set will perform spectrum sensing and send the sensing results to the FC. Based on the sensing results, the FC uses the majority-rule to determine whether the PU is active to improve accuracy:

$$State = \begin{cases} busy & \sum_i I_{\{O_i=1\}} \geq \sum_i I_{\{O_i=0\}} \\ idle & \sum_i I_{\{O_i=1\}} < \sum_i I_{\{O_i=0\}} \end{cases} \tag{21}$$

where $I_{\{O\}}$ is the indicator function, which is equal to 0 if O is true and 1 otherwise, and O_i is the sensing result of SU_i.

Based on this, different SUs can be grouped according to different states for spectrum sensing. Compared with other schemes that only select some SUs with high detection probability for spectrum sensing, the proposed scheme can alleviate the life-cycle termination caused by continuous sensing of some SUs.

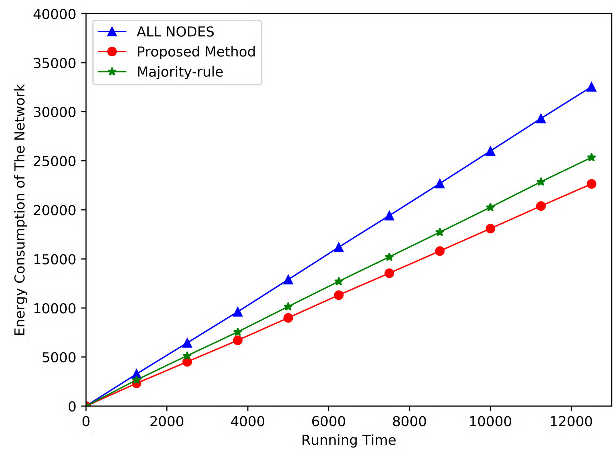

FIGURE 6. Energy consumption of network (with transition probability 0.5).

V. SIMULATION AND ANALYSIS

This section evaluates the performance of proposed HMM-based Cooperative Spectrum Sensing scheme in terms of energy consumption and spectrum utilization through simulation study. The *transition probability*, R_T^i, is defined as the frequency the state of channel for PU_i changes from unoccupied to occupied. R_T^i can be used as a metric for PU activity, thus the simulations are performed in different licensed channels with R_T^i from 0.2 to 0.8. The simulation environment consists of 10 SUs deployed within a $50m \times 50m$ monitoring area. In order to fully establish the state of the HMM, each SU is assumed to have an overlapping communication area with at least one other SU. Furthermore, both energy consumed by an SU during the spectrum sensing phase and the traffic throughput per transmission are normalized to one for visual comparison.

Prediction methods based on majority-rule [15] and "ALL NODES" are used for comparison. In the former method, if more than 50% of SUs' prediction results of the channel status is busy, all SUs will stop performing spectrum sensing during next time slot. In the latter method, all SUs perform spectrum sensing every time slot without any cooperative and prediction-based methods. The length of the observation is set to 150, and the simulations run for over 12,000 rounds.

Fig. 6 compares energy consumption of the proposed method against the other two methods when R_T^i is set to 0.5. As can be seen, energy consumptions of the proposed scheme and the majority-rule method are lower than the "ALL NODE" method. This is because the "ALL NODE" method performs spectrum sensing every time slot resulting in higher energy consumption. Meanwhile, the energy efficiency of the proposed method is better than the majority rule method where all the SUs either perform spectrum sensing or not during each time slot. If the result of the majority rule is to sense the spectrum, but there are still many SUs affected by the PU, the energy consumption will increase. In contrast, the proposed scheme can manage SUs belonging to the IP set

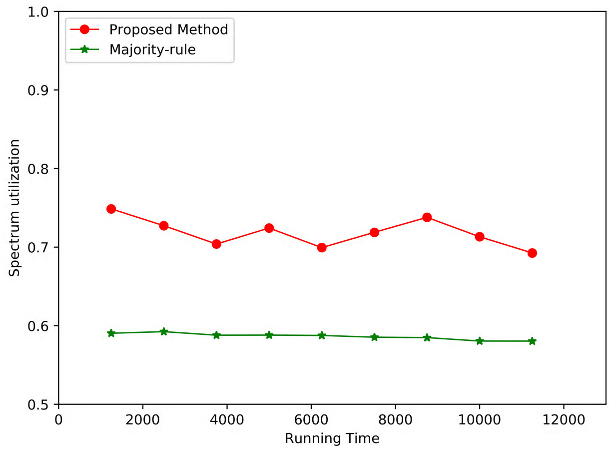

FIGURE 7. Spectrum utilization of network (with transition probability 0.5).

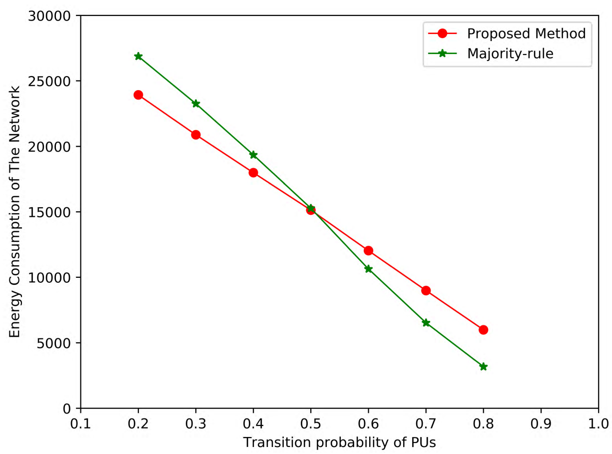

FIGURE 8. Energy consumption with different transition probability.

to not perform spectrum sensing during the next time slot, thereby decreasing energy consumption.

Changes in the frequency of spectrum sensing will inevitably affect spectrum utilization. Fig. 7 shows that the proposed scheme outperforms the majority rule method in terms of spectrum utilization. The reason is that all SUs are prevented from performing spectrum sensing causing SUs that did not detect a PU to lose transmission opportunities.

Fig. 8 shows how the energy consumption varies as a function of the transition rate. The energy consumption of the majority rule and proposed schemes decrease as the transition rate increases. The reason is as PUs' activity increases SUs' transmission opportunities decrease. When R_T^i exceeds approximately 0.5, the energy consumption of the majority rule method becomes lower than that of the proposed scheme. However, Fig. 9 shows that as the transition probability increases, the spectrum utilization of the proposed scheme averages around 0.75, while the spectrum utilization of the majority rule method decreases. The reason is that the proposed scheme can still schedule some SUs to perform spectrum sensing while most SUs are predicted to interfere with PUs, thus some level spectrum utilization can be maintained.

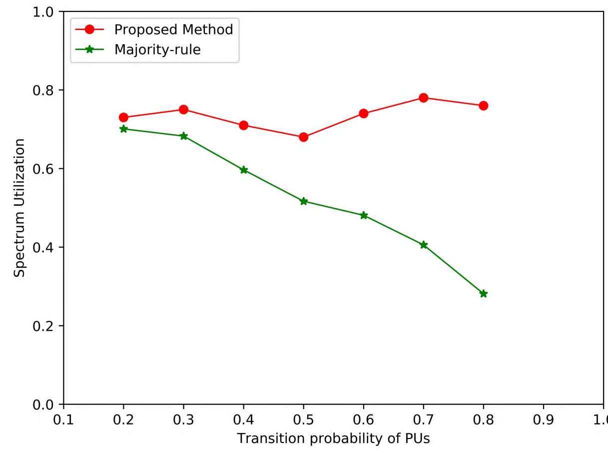

FIGURE 9. Spectrum utilization with different transition probability.

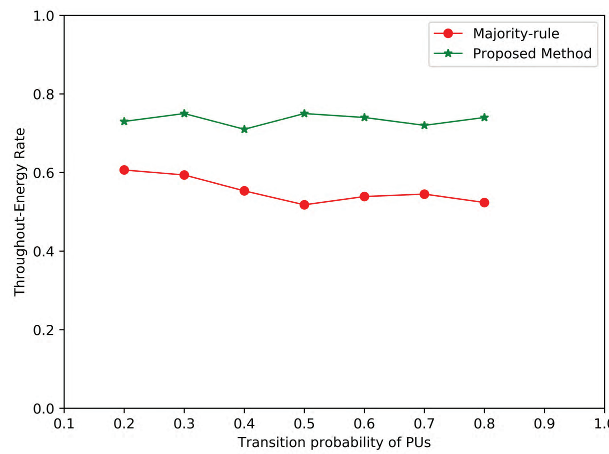

FIGURE 10. Throughout-energy rate with different transition probability.

Meanwhile, the majority rule method will force all the SUs to stop spectrum sensing, thus the spectrum utilization decreases. Although this approach reduces energy consumption, it also reduces spectrum utilization. This relationship can be defined using the throughput-energy rate, which is given as

$$\frac{\sum_{i=0}^{n} Throughput^i}{\sum_{i=0}^{n} E_T^i}, \tag{22}$$

where n is the number of SUs performing spectrum sensing and transmission, and

$$Throughput^i = \begin{cases} 1 & \text{transmission of SU}_i \text{ is present} \\ 0 & \text{transmission of SU}_i \text{ is absent} \end{cases} \tag{23}$$

In other words, high throughput and low energy consumption will result in higher throughput-energy rate and thus better network performance.

Fig. 10 shows that the proposed scheme has a higher throughput-energy rate compared with the majority rule method, which means the proposed scheme can achieve higher throughput with the same energy consumption. Therefore, the proposed scheme reduces energy consumption and improves spectrum utilization. In particular, when the transition probability of PUs increases, which indicates increased activity of PUs, the better network performance can be maintained where the proposed scheme has average 15% improvement in throughput-energy rate compared with the majority rule method.

VI. CONCLUSION

This paper introduced a spectrum prediction algorithm based on HMM for a cognitive radio network, where SUs have overlapping communication areas. By combining observations from multiple SUs and setting the states to zones affected by the PUs, the prediction problem of a network can be addressed as an N-state HMM problem (for $N>2$) compared with just 2 states in traditional schemes. Moreover, cooperative spectrum sensing is performed by scheduling SUs with the same future state, thereby improving the detection accuracy. A simulation study was performed to verify the performance of the proposed method in different environments. However, our experiments are still not sufficient. As a future work, due to the higher complexity of the Baum-Welch algorithm, a more detailed analysis on the multi-SU environment will be performed. At the same time, the prediction performance of our network structure model will be improved using different algorithms.

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