Residual Cigarette Recycle System Spectrum Switching Based on Markov Model

Shunkai Sun 1,3,*, Jie Li 1, Qi Xu 1, Jiule Zhu 2, Weilin Cao 1, Haitao Chen 1, Ruidong Liu 1 and Wangdi Hu 1

1 Ningbo Cigarette Factory, China Tobacco Zhejiang Industrial Co., Ltd., Ningbo 315504, China;
2 College of computer and software, Nanjing University of Information Science and Technology, Nanjing 210044, Jiangsu, China
3 Faculty of Electrical Engineering and Computer Science, Ningbo University, Ningbo 361102, China;
Email: shunkaisun@126.com

Abstract. In the process of communication of residual cigarette recycle system, due to the residual cigarette recycling bin WIFI switch with the signal strength, signal quality, distance of WIFI and other reasons. In order to keep the residual cigarette recycling bin in a non-inductive switching state, WIFI needs to adopt seamless Switching technology [1]. In which cognitive radio automatic networking (CRAN) is one of the core technologies, in order to suppress cognitive users from interfering with authorized users, it is necessary to reduce WIFI switching times as much as possible. Advance a cognitive wireless dynamic WIFI switching method based on the detection of the WIFI channel idle time (PWCIT). The theory is based on a known-state sequence hidden Markov [2] model (KSS-HMM). The selection method of the alternative WIFI is given, and the optimal channel is selected for data transmission by comparing the data transmission throughput of each candidate WIFI. The simulation results show that compared with the traditional channel selection method and the random channel [3] selection, the method can significantly reduce the number of WIFI handovers and improve the throughput of cognitive [4] users.

1. Introduction
Residual cigarette recycling fully reflect the intelligence of tobacco industry [5]. As the demand for wireless broadband access services in the cigarette industry continues to increase, the wireless WIFI handover speed requirements are getting higher and higher. Basis an investigation report released by the IEEE, the spectrum utilization rates [6] of licensed bands in different space at different times vary widely, ranging from 12% to 90%. According to IEEE engineer Garcia's research, "Observe a whole 2.4 GHz spectrum at any time, you will find that about 92.5% are idle." Therefore, WIFI encounter a problem of shortage and waste of spectrum resources. Cognitive radio (CR) technology proposed by RABINER L [7] in 2005, which can effectively improve the utilization of spectrum resources. The CR consists of a key user (KU) network and an affiliated user (AU) network that improves spectrum utilization by allowing the AU to temporarily access the licensed spectrum that is not used by the KU.

In the CRAN network [8], the spectrum switching technology of cognitive users determines the capacity of the system and the utilization of the spectrum. When the transmission of the affiliate user is interrupted by the key user, if the AU arbitrarily selects one channel whose current time is idle, it is likely to select one channel with high KU utilization [9]. The method is based on the known state
sequence hidden Markov model (KSS-HMM), predicts the future channel idle time expectation value and the number of transmitted data packets, and obtains an alternative channel set if the AU needs to be performed [10]. Spectrum switching, comparing the amount of transmission data of the candidate channel to determine the target channel of the handover.

2. System Model

2.1. Residual Cigarette Recycling Bin

The size of the residual cigarette recycling bin together with the static weighing module and the pallet is 1200×1100×1400 mm; the residual cigarette recycling bin material is stainless steel; the single recycling bin carries: 160kg. The AGV trolley is used to carry the support wheels of the pallet. Four static weighing modules are arranged on the pallet, and the four static weighing modules are connected with the external four legs of the residual cigarette recycling bin made of stainless steel. The residual cigarette recycling bin is in the form of a three-sided hinged door, as figures 1.

![Figure 1](image1.png)

**Figure 1.** Schematic diagram of the three-dimensional structure of the residual cigarette recycling bin.

2.2. Predictive Spectrum Switching Process

The AU establishes a prediction model of the channel state by observing the past state of the channel, predicts the spectrum usage, and ensure maximum spectrum utilization. As a result, AU needs to use a better PWCIT method to make the choice of channel. Figure 2 shows the two channel selection scenarios, good channel selection (i.e. PWCIT channel switching) and poor channel selection. First, the affiliate user A (AU_A) transmits data on channel 3. When the first time is interrupted by KU_B, the AU_A detects that each channel only finds that channel 2 is an idle channel, and the AU_A switches from channel 3 to idle channel 2. And has a transmission delay of 1 slot. Channel second handover, the AU_A on channel 2 detects that both channel 1 and channel 3 are idle channels, and a good channel selection method selects a longer duration from the current time to the next KU interruption time. The poor channel selection method, selects a channel with a shorter time slot in the future. For poor channel selection, the AU_A needs to be switched multiple times for complete packet transmission. Assuming that there is a time slot switching delay for each handover, a good channel selection method will increase the throughput of the AU while reducing the interference to the KU.

![Figure 2](image2.png)

**Figure 2.** The WiFi channel handover process
2.3. Hidden Markov Model (HMM)

The Hidden Markov Model (HMM) is a multi-random channel switching process, one of which is a hidden state transition sequence, which corresponds to a simple Markov process; the other is an observation sequence related to the hidden state. S is assumed to be a state set of hidden channels composed of N states, a WIFI channel state $x_t \in S$ at time $t$, $Z = \{ a_{ij} \}$ is a channel state transition probability matrix of $N \times N$; $V$ is an AU detection consisting of $M$ states. The channel state set detected by AU at time $t$ is $y_t \in V$, $T = \{ b_i(k) \}$ represents the conditional probability matrix of the hidden channel state is $a_i \in A$, and the AU detected channel state $y_k \in V$; $\pi = \{ \pi_i \}$ is the channel initial state distribution matrix; then the HMM model can be described as $\lambda = \{ Z, T, \pi \}$.

2.4. Known State Sequence Hidden Markov Model (KSS-HMM)

In the KSS-HMM model, channel idle and busy states are represented by '0' and '1', respectively. Suppose there are $N$ hidden states ($N$ is large enough), and its hidden state system model is shown in Figure 3. Suppose the initial state $\pi(00) = \pi(01) = \pi(10) = \pi(11) = 0.25$, $M = 4$, the hidden channel state set condition $A = \{-q,...,0,1,...,p\}$, the channel state set $V = \{00, 01, 10, 11\}$ detected by AU, the observation sequence is $y^T = \{ y_t, t = 1, ..., T, y_t \in V \}$, and the hidden state observation sequence is $x^T = \{ x_t, t = -1,0,1,...,T, x_t \in S \}$, calculate the state transition estimation parameters of the above model:

\[
\hat{e}_{mn} = \frac{\phi_{mn}(x(t-n))}{\sum_n \phi_{mn}(x(t-n))} \quad (1)
\]

\[
\hat{f}_{kn} = \frac{\phi_{kn}(y(t-n))}{\sum_n \phi_{kn}(y(t-n))} \quad (2)
\]

The channel state transition probability matrix is $E = \{ e_{ij} \}$, as in the following form:

\[
e_{ij} = \Pr(x_t = s_i | x_{t-1} = s_j) \quad (3)
\]

After the observation of $T$ time, the obtained data can calculate equations (1) and (2). The matrix $F = \{ f_{j(k)} \}$, as in the following form:

\[
\begin{align*}
  f_j(1) &= e_{j+1}, & f_j(0) &= e_{j}, & j > 0 \\
  f_j(0) &= e_{j-1}, & f_j(1) &= e_{j,0} & j \leq 0
\end{align*}
\]

\[(4)\]

Figure 3. KSS-HMM Hidden State Channel Switching Model

2.5. System Model of PWC IT Spectrum Switching Method Based on KSS-HMM

Consider the case where 1 AU accesses multiple KU channels. In a fully covered wireless AP network, assume that each KU is an M/G/1 system, that is, the KU obeys the Poisson arrival process with the parameter $\lambda_p$, and the service time of the KU satisfies the parameter $\eta_p$. Exponential
distribution, KU service time can be evaluated. Assuming that the wireless node is capable of adaptive modulation and coding, \( \{N_{R1}, N_{R2}, \ldots, N_{RN}\} \) be the modulation coding parameter, which is a function of WIFI distance and wireless device layout. The cell is divided into \( N \) concentric rings, each concentric ring has a radius of \( R_i \), \( i = 1, 2, \ldots, N \), and each concentric ring has \( K \) channels, and there is a set of concentric rings \( R_1 = \{1, 2, \ldots, N\} \), the bandwidth of WIFI is \( B \). set \( r \) be the coding rate, the distance between the mobile node and WIFI is \( r_{BW} \), and the spectral efficiency \( [14] \) is:

\[
\eta(r_{BW}) = r \log_2 \left( N_{rw} + N \right) \quad (b/s/Hz)
\]

The \( j \) channel capacity in the \( i \) ring is \( C_{ij} \), namely:

\[
C_{ij} = \eta(r_{BW}) \frac{B(N_{rw} + N)}{KN} \quad (b/s)
\]

Then the AU service rate of the \( j \) channel in the \( i \) ring is:

\[
\gamma_{ij} = \frac{C_{ij}}{G} \left( p/s \right)
\]

As in the following form: \( G \) is the size of the AE packet. In each channel, hidden from \( t=1 \) to \( t=T \), the probability of observing the sequence is:

\[
Pr(x') = \sum_{t=x'}^T a_{x, t} b_{x_t}
\]

As in the following form: \( x_0 \) is the hidden state of the channel at time \( t=t_0 \). Given the hidden state sequence \( x' \), the conditional probability of the observed state sequence \( y' \) from \( t=x' \) to \( t=T \) is:

\[
Pr(y' | x') = \sum_{t=x'}^T \left( x' | y' \right)
\]

The probability of observing the sequence \( y' \) from the multiplication theorem and the edge distribution law is:

\[
Pr(y') = \prod_{t=1}^T Pr(x', y') = \prod_{t=1}^T Pr(x' | y') Pr(x') = \sum_{t=x'}^T \prod_{t=1}^T Pr(x' | y') a_{x, t} b_{x_t}
\]

(10)

It can be seen from the KSS-HMM that the hidden state observed in the past and the detected channel state are uniquely determined. Therefore, as can be seen from (10), if the AU needs channel switching at time \( t=t_0 \), the probability of the observation sequence with the length of each channel slot being \( T_1 \) is:

\[
Pr\left(y_{1}^{T_1}\right) = \prod_{t=t_0}^{t_0+T_1-1} a_{x, t} b_{x_t} \left( y_t + y_{t_0-T_1+1} \right)
\]

(11)

As in the following form: \( y_{1}^{T_1} \) is the sequence of observation states with a slot length of \( T_1 \), ie \( y_{1}^{T_1} = \{y_t, t=t_0-T_1+1 \ldots, t_0, y_t \in V\} \). The probability that the channel is idle in the range of the time slot after the time \( t_0 \) is \( T_2 \) is:

\[
Pr\left(y_{2}^{T_2}\right) = \prod_{t=t_0+T_1}^{t_0+T_2} a_{x, t} b_{x_t} (t_0-T_1+1)
\]

(12)
As in the following form: \( y_{T_2} \) is the sequence of observation states with a slot length of \( T_2 \), i.e.
\[
\{ y_{t_i}, t_i = t_0 + 1... t_0 + T_2, y_i \in V \}. 
\]
Then, the joint probability of the time slot length \( T_1 + T_2 \) of \( t = t_0 + T_1 + 1 \) to \( t = t_0 + T_2 \) is:
\[
\Pr\left( y_{t_i}^{T_1}, y_{T_2} \right) = \prod_{t_i = t_0}^{t_0 + T_1} a_{y_i} b_{y_i} \left( y_i + y_{t_i - T_1 + 1} \right) \prod_{t_i = t_0 + T_1}^{t_0 + T_2} a_{y_i} b_{y_i} \left( t_i - T_1 + 1 \right)
\]
(13)

Knowing the observation sequence \( y_{T_1} \), the channel's future idle time expectation is:
\[
E(T_2) = \sum_{t_i = t_0 + T_1}^{t_0 + T_2} T_2 \Pr\left( y_{t_i}^{T_1}, y_{T_2} \right)
\]
(14)

Based on the above calculation, the criterion for the AU on the channel \( m \) to be switched to the new channel is:
\[
\Pr_m \left( y_{t_i}^{T_1}, 1 \right) < \tau_L
\]
(15)

As in the following form: \( \tau_L \) is the minimum threshold at which the channel is considered to be busy. In addition, the condition that channel \( l \) becomes an alternate channel is:
\[
\Pr_m \left( y_{t_i}^{T_1}, 0 \right) \geq \tau_H
\]
(16)

As in the following form: \( \tau_H \) is the probability threshold for the channel to be considered idle. BU is a set of channel selections for devices, and the optimal channel is selected from the candidate channels:
\[
Ch_n = \max_{j \in BU} \mu_j \times E(T_2)_j
\]
(17)

### 3. Simulation Results and Analysis

The PWCIT spectrum switching method is simulated with MATLAB to evaluate its performance and compared with the intelligent switching method [6] and stochastic switching. In the simulation, suppose channel selection is completed under ideal conditions, that is, there is no noise interference; the activity of KU is a M/G/1 queueing model, that is, the KU obeys the Poisson arrival process with the parameter \( \lambda_p \), assuming the KU packet length both the length of the AU packet and the AU packet are subject to the Weibull distribution. The channel state consists of a training sequence and a history sequence. The simulation parameters of the spectrum switching residual smoke recovery system are shown in Table 1.

**Table 1. Simulation parameters**

| Channel transmission rate | 1 Mbps | Time slot length | 1ms |
|---------------------------|--------|-----------------|-----|
| AU Packet length          | 10^6bits | KU Packet length | 8 x 10^8bits |
| \( \tau_L \)              | 0.6    | \( \tau_H \)    | 0.6 |
| Training time             | 1500s  | Historical time  | 1000s |
| \( T_1 \)                 | 100ms  | Switching delay | 1ms |

Figure 4. simulates a comparison of channel selection methods for different channel numbers. The number of channels varies from [8, 32]. Compared with the intelligent and stochastic switching methods, when there are 8 channels, the number of channel switching times of PWCIT is reduced by 62.1% and 20% respectively. When there are 32 channels, the PWCIT number of channel switchings has dropped by 200% and 105.3%. As the number of channels increases, the number of switching
channels decreases. This is because the more the number of channels, the greater the chance that the continuous idle length in the channel is $T_2$, and the larger the expected value $E(T_2)$, the fewer the number of channel switching.

![Figure 4](image4.png)

**Figure 4.** Comparison of the number of channel switching times in the case of different channel numbers.

Figure 5 shows a comparison of the three switching methods for AU at different KU arrival rates $\lambda$. As the $\lambda$ of KU increases, the number of channel switching times of the three methods increases continuously, because KU appears more frequently in the system, and the transmission of AU is more likely to be interrupted by KU. When $\lambda=0.08$, the number of PWCIT switching is reduced by 72.2% and 33.3% compared with stochastic switching and intelligent switching. When $\lambda=0.72$, it is reduced by 225.9% and 125.3%. As can be seen from the figure, the greater the $\lambda$, the more obvious the improvement of PWCIT compared to stochastic switching.

![Figure 5](image5.png)

**Figure 5.** Comparison of channel switching times with different KU arrival rate $\lambda$

Figure 6 shows that the throughput of PWCIT is significantly increased compared to intelligent or stochastic switching when the AU throughput varies with the number of channels in the range [8, 32]. When the number of channels changes within the range of [8, 32], the trend of intelligent handover and random handover throughput tends to be stable, while the PWCIT handover throughput growth trend continues to increase. This shows that the PWCIT handover method can obtain better throughput when the number of channels increases.
Figure 6. Comparison of AU throughput of three channel switching methods under different channel numbers

4. Conclusion
A residual cigarette recycle system based on KSS-HMM PWCIT cognitive radio automatic networking spectrum switching is proposed. The simulation results show that compared with the intelligent and stochastic handover methods, the PWCIT handover method greatly reduces the number of channel handovers, because the method comprehensively predicts the channel idle probability size, the idle time length, and the channel service rate. In addition, the PWCIT switching method reduces the AU throughput and improves the real-time performance of the AU data transmission, thereby achieving a stable connection between the residual cigarette recycle system and the WIFI. Channel prediction methods will be further optimized in future research, and the impact of false alarm rate and missed detection rate on channel switching will be considered.

5. References
[1] Kiyohide Nakauchi; Yozo Shoji. WiFi Network Virtualization to Control the Connectivity of a Target Service. IEEE Transactions on Network and Service Management, 2015, 6, pp. 308-319.
[2] Matthew Richardson; Pedro Domingos. Markov logic networks. Machine Learning, 2006, 2, pp. 107–136.
[3] Changlin Yang; Kwan-Wu Chin; Ying Liu. On Maximizing Sampling Time of RF-Harvesting Sensor Nodes over Random Channel Gains. Publisher: IEEE, 2018, 6, Kansas City, MO, USA.
[4] Francesca Bertacchini; Eleonora Bilotta; Maria Carmela Lombardo; Marco Sammartino; Pietro Pantano. The European Physical Journal Special Topics, 2018, 10, pp. 787-797.
[5] van der Eijk Y, Bialous SA, Glantz S. The Tobacco Industry and Children's Rights. Europe PMC, 2018, 5.
[6] Hideaki Takagi. Detailed Analysis of the Response Time and Waiting Time in the M/M/m FCFS Preemptive-Resume Priority Queue. International Conference on Queueing Theory and Network Applications, 2015, pp. 3-7.
[7] Ching-MienWu; Pei-TsengKung; Chia-IngLi; Wen-ChenTsai. The difference in medical utilization and associated factors between children and adolescents with and without autism spectrum disorders. Research in Developmental Disabilities, 2015, 1, pp. 78-86.
[8] RABINER L; Noninvasive cardiac quantum spectrum technology effectively detects myocardial ischemia. Medical Science, 2005, 1, pp. 1542-1562.
[9] Tong Shi; Yikang Wang; Linfeng Wan; Xin Cheng. PREDICTING THE ARRIVAL TIME OF CORONAL MASS EJECTIONS WITH THE GRADUATED CYLINDRICAL SHELL AND DRAG FORCE MODEL. The Astrophysical journal, 2015, 06. Volume 806, Number 2.
[10] HaitaoZhou; JinChen; GuangmingDong; RanWang. Detection and diagnosis of bearing faults using shift-invariant dictionary learning and hidden Markov model. Mssp, 2016, 05. pp. 65-79.