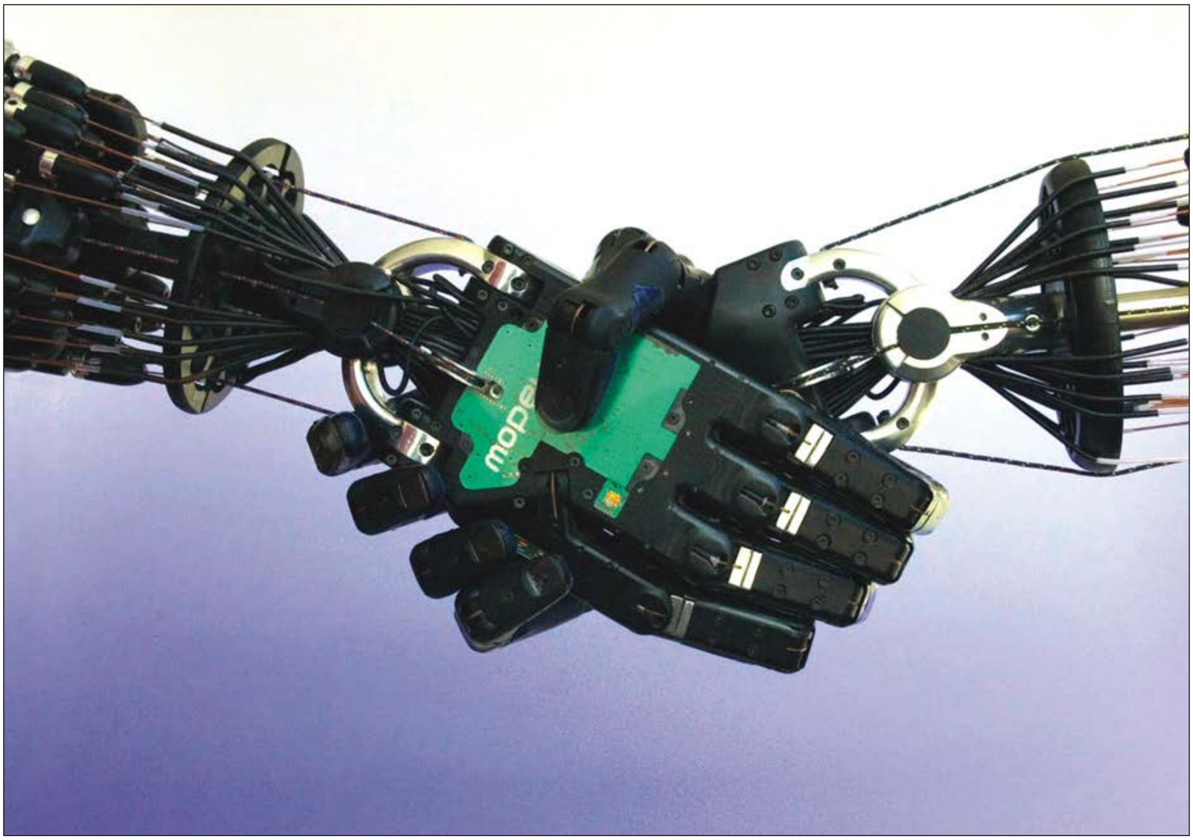

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Research Article
Intelligent Selective Spectrum Access in Cognitive Radio Networks

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Abstract
Wireless communication technology had enabled numerous services that had placed the current radio frequency bands at scarce. Thus, with the emerging of cognitive radio paradigm, the next generation network is determined to increase spectral efficiency in order to satisfy the wireless services demand. In this study, we proposed a novel solution that optimized the performance of cognitive radio networks that is mainly affected by spectrum sensing and channel selection process. Traditionally, secondary users randomly sense the channels until an idle channel is detected whenever their transmission is being interrupted. Inaccurate detection of spectrum availability had caused delays, throughput degradation and high spectrum handoffs in cognitive radio network. Consequently, this study proposes a novel use of Hidden Markov model for recognition of primary user traffic patterns. Next, prediction of an idle channel selection scheme is being proposed. The main concerned of this scheme is to prevent unnecessary delays in finding spectrum opportunities, reduce the number of primary user collision and number of handoffs. Hence, efficient and successful utilization of unexploited radio resources can be realized. Simulation results clearly verify that by using this proposed solution, the performance of cognitive radio network can be improved in terms of successful channel utilization, primary user collision, delays and number of handoffs.

Key words: Hanoffs, CRN, PU, SU, HMM

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INTRODUCTION

Federal Communications Commission (FCC) had reported up to 85% of the assigned spectrum is underutilized. This is due to the current fixed spectrum allocation policy[1]. The unexploited spectrum had cause a waste of radio resources. Meanwhile, the increasing demand of spectrum resources for wireless communication and multimedia had caused spectrum scarcity in current fixed spectrum policy. Thus, Cognitive Radio Network (CRN) is an emerging technique that promised an efficient spectrum utilization[2] to encounter this issue.

The CRN is a dynamic spectrum access technology which enables other wireless users besides the licensed users to share the licensed spectrum in an opportunistic manner. These other users that are commonly known as Secondary Users (SU) are capable of opportunistically access the licensed spectrum while carefully avoiding harmful disruption to the Primary Users (PU) which is the licensed users. However, the SUs must vacate the occupied channel immediately whenever the PUs appears to claim back the channel. The PUs has the preemptive priority to use the licensed spectrum. The CRN is first envisioned by Mitola and Maguire[3] to provide high bandwidth to wireless users via heterogeneous wireless architectures and dynamic spectrum access techniques.

There are namely four essential functions in CRN[2]. They are spectrum sensing, spectrum decision, spectrum sharing and spectrum handoff. Spectrum sensing objective is to observe the spectrum occupancy state and identify the channel availability, while SUs opportunistically access the available channels strategically by enforcement of spectrum decision, spectrum sharing and spectrum mobility. Thus, of course, the problem of processing delays will occur in these four functions. Thus, to improve the efficiency of spectrum utilization, spectrum sensing and handoff decision for CRN has been extensively studied in the literature.

The PU detection is executed in spectrum sensing to check the channel availability and prevent harmful interference to PU by SUs. One of the popular methods for spectrum sensing is energy detection. This is due to its simplicity in terms of implementation. However, the performance of the energy detector is subject to uncertainty in noise power. Energy detectors also frequently generate false alarms due to unintended signals because they cannot differentiate the signal types[2]. Nevertheless, accuracy and robustness of spectrum sensing algorithms are vital to cognitive radio. Many literatures had proposed algorithms and technique to overcome these limitations while using energy detection[4]. One of the most popular methods studied in the literatures is cooperative detection[2,5,6]. It has been shown that by exploiting multiuser diversity, cooperative detection capable to overcome the issues of hidden PUs, shadowing and multi-path fading and thus achieves better detection performance than only a single user sensing[6]. Even so, the overhead traffic required by cooperative scheme had adverse effects on resource-constrained networks[2].

On the other hand, Wang and Wang[7] studied two types of handoff known as reactive and proactive schemes. In the reactive schemes, instantaneous channel handoff to a new channel is executed only after sensing a PU in the current operating channel band. While, in the proactive schemes, spectrum handoff is executed on a pre-selected channel by SUs before a PU emerges in the channel. In proactive schemes, strategic handoff decision can be made resulting better network performance. However, the problem in proactive scheme is that the pre-selected target channels may no longer be available when interruption event occurs[8]. Although, reactive handoff scheme consumes time to find available channels; sensing results are more reliable and accurate.

Therefore, in this study, we were interested in proactive handoff schemes. However, to overcome the issues of the pre-selected channels to be reliable when perform switching; we proposed to inherit the process of learning and prediction to select available channels. It is known that PU traffic pattern show different characteristics in wireless network. Thus, CRN needs to characterize spectrum bands by considering current radio conditions as well as PU activity to select a suitable channel. An intelligent channel selection is needed to optimize efficient SU transmission time by comprehensively considering spectrum sensing capabilities and channel characteristics[9]. In this study, we will investigate the learning in spectrum selection decision to alleviate the issue of inaccuracy of PU detection. An accurate prediction of the availability of channel bands helps in strategic planning of network resources as well as guaranteed quality of service.

In our study, we will employ proactive handoff decision by investigating the prediction of PU appearance and channel availability using Hidden Markov Model (HMM). The HMM will be used to characterize the PU traffic pattern in a spectrum band. HMM parameters will be estimated to select suitable channel for next channel selection decision. This method will eventually reduce the number of handoffs and delay in finding idle channels. Our major contributions are as follows: (1) A novel channel selection scheme is proposed for CRNs based on the prediction algorithm using HMM, (2) During the channel ordering design, joint longest idle channel and highest likelihood of being idle is adopted to enhance the selection of a channel and (3) Comprehensive simulation is implemented in order to evaluate our scheme compared to traditional channel selection algorithms.

MATERIALS AND METHODS

System model description: In this study, there are two types of users in CRN: (1) A PU operating at each licensed channel, (2) A SU that seeks and can use the channel whenever it is available. It is assumed that time is divided into slots of duration t. We assumed a discrete timeslot model, where each timeslot takes values in {0, 1,.., T}. The spectrum of interest consists of S channels with identical bandwidth, B Hz. Energy detection method is being used to do spectrum sensing and the average signal-to-noise ratio (SNR) is assumed to be fixed. The energy detector measures the signal power at each channel band periodically and compares with a predefined threshold. Spectrum sensing at each channel is perform to determine the state, M {1, 0} at every timeslot. This is to determine the availability of the channels for SU operation without harming the operating PU. Idle and busy channel is shown as state 0 and state 1, respectively. Spectrum sensing will output state M of each timeslot of each channel. SU will record the sensing output as the observation data to our scheme that able to describe the PU availability in each channel. It has sufficient information to determine the periodicity and occupancy of the channel.

We assume that each PU accesses the licensed channel modeled as an alternating renewal two state birth-death model with birth rate α and death rate β[9]. An on/off state represents a PU occupying a channel. The channel state alternate between state on (busy) and state off (idle). The SU can transmit only during the off time slots. Each channel follows the exponential on/off distribution[10]. The probability density function of the time intervals for the on/off states, respectively satisfy:

$$f_{ON}(t) = \begin{cases} \beta e^{-\beta t} & t \geq 0 \\ 0 & t < 0 \end{cases} \tag{1}$$

$$f_{OFF}(t) = \begin{cases} \alpha e^{-\alpha t} & t \geq 0 \\ 0 & t < 0 \end{cases} \tag{2}$$

The probability of channel availability is the normalized period that is available for SU. Let pon denote the probability of and idle channel. Then:

$$p_{on} = \frac{\beta}{(\alpha + \beta)} \tag{3}$$

The purpose of this prediction algorithm is to provide intelligence to CRN just as the prerequisite in Mitola and Maguire[3] to create robustness to network environment. This algorithm will prioritize which channel to be sensed in order to reduce processing delay. Prior to SU transmission, spectrum sensing is still required. This is to further avoid inaccuracy in state prediction and misdetection in detecting available data.

Hidden Markov model: The Hidden Markov Model (HMM) is a powerful statistical technique that has become increasingly popular over the last few decades. Since the models are very rich in mathematical structure, they can form the theoretical basis for use in a wide range of applications[11]. The HMM is used for modeling and analyzing time series or sequential data in various fields today, such as automatic speech recognition, cryptanalysis, natural language processing, computational biology, bioinformatics, etc. With its prior knowledge, HMM is mainly concerned on the unobserved sequence of hidden states and the corresponding sequence of related observation. An HMM is described in respect to hidden states, observations and their model probabilities. Thus in CRN, the true state of channel occupancy is the hidden state since the sensing sequence which is the past observation data is a disrupted energy signal by noise in the channels. Therefore, the real occupancy of the channel is not known to SUs, N = {0,1}. By feeding the past observation data, M = {0, 1} to the system, PU activities in the channel will be modeled using HMM parameters. These parameters will then be used for channel occupancy prediction for future channel selection. HMM modeling for licensed network was proven its validity in study[12].

It is mentioned before that HMM is first fed with past observation sequence of data and trained to find the optimal HMM parameters. These parameters (λ = A, B, π) are consists of state transition matrix, A, state observation matrix, B and initial state distribution, π. State transition matrix, aij and state observation matrix, bj (Ok) is defined:

$$\alpha_{ij} = p[q_{t+1} = S_j | q_t = S_i],\ 1 \leq i,\ j \leq N \tag{4}$$

$$b_j(O_k) = P[O_k | q_t = S_j],\ 1 \leq j \leq N,\ 1 \leq k \leq M \tag{5}$$

The goal of training is to adjust the HMM parameters above, such that the PU observation are best represented by the model, P(O|λ). As described by Rabiner[11], there are three basic problems in HMM estimation training need to be solved in order to be useful in real world applications. The first problem is to compute the likelihood probability of the observation sequence is best defined by the model. The second problem is to find the best hidden state sequence, $q = \{q_1, q_2, q_3,... q_T\}$ given by the model, λ. This can be done by using dynamic programming, Viterbi algorithm. By finding the quantity, $\delta_t(i) = \max_{qt} P [q_1, q_2... q_1 = i, O_1, O_2... O_t|\lambda]$, the best actual state sequence can be retrieved. Lastly, the third problem is to optimize the parameters, $P(O|\lambda)$ based on the observation sequence, $O = \{O_1, O_2, O_3,.. O_T\}$. The first problem is normally solved by using forward-backward algorithm while the third problem is solved by Baum-Welch method[11], which is a well-known iterative procedure and is basically a derived form of the Expectation-Maximization (EM) algorithm for HMMs.

HMM prediction model: In this study, we propose a generic channel selection spectrum access framework as shown in Fig. 1 to carry out a learning and selective spectrum sensing and access. This intelligent spectrum access enables an SU to sense and select target channel in an optimal order while maximizing spectrum utilization and handoff performance. This is accomplished with the aid of idle channel prediction, which allows an SU to determine the optimal channel-sensing order by taking into account the probability of a channel appearing idle in the next time slot and the length of idle period.

Observation data sequence, $O_{1,2}\cdots_T$ where, T is the length of the sampling instant, is collected at each sensing period that takes place at each time slot. At the learning stage, the SU will use the observation sequence and estimate the HMM model parameters, λ. Then by using λ, the SU will predict the PU appearance for time slot $T+t_d$. Length of the idle period, td is calculated for channel selection process. The main advantages of this proposed framework is the SU will correct and adjust the channel state history record accordingly. Hence, the training of HMM parameters will be optimized.

In practical implementation of spectrum sensing, the sensing results will be imperfect due to various reasons such as hardware impact and noisy channels. The imperfect sensing may create errors in the form of false alarms and missed detections[2] causing misidentification of channel availability. Hence, the statistical information fed to the HMM training will be inaccurate and will result error in prediction. Thus, we employed a novel procedure where an SU will immediately stop transmitting in a selected channel (misdetection occurs) when a PU collision occurred during transmission. Then, the SU will be inform and correct the observation sequence of that current timeslot. HMM training will be executed again to update $\hat{\lambda}$ for further channel estimation and prediction. This procedure will help to increase the accuracy of channel prediction by jointly take into account the sensing errors and SUs transmission collision. Though, the accuracy of the training algorithms also affected by the initialization of HMM parameters due to the nature of BW always converge to local minima[11]. For channel state prediction, the observation sequence will be fed into Viterbi algorithm to correct the data sequence. Then by taking this update sequence, we predict channel occupancy by finding the likelihood probabilities of $P [O_{T+1} = 1|\lambda]$ and $P [O_{T+1} = 0|\lambda]$. This is done by computing forward variable, ϕ, by looking wd of previous observation as follows, Initialization:

$$\Phi_1 (i) = \pi_i b_i (0_1), 1 \le i \le N \tag{6}$$

Induction:

$$\varphi_{t+1}(j) = \left[\sum_{i=1}^{N} \varphi_t(i)\pi_{ij}\right] b_j(0_{t+1}), 1 \le t \le T, 1 \le j \le M \tag{7}$$

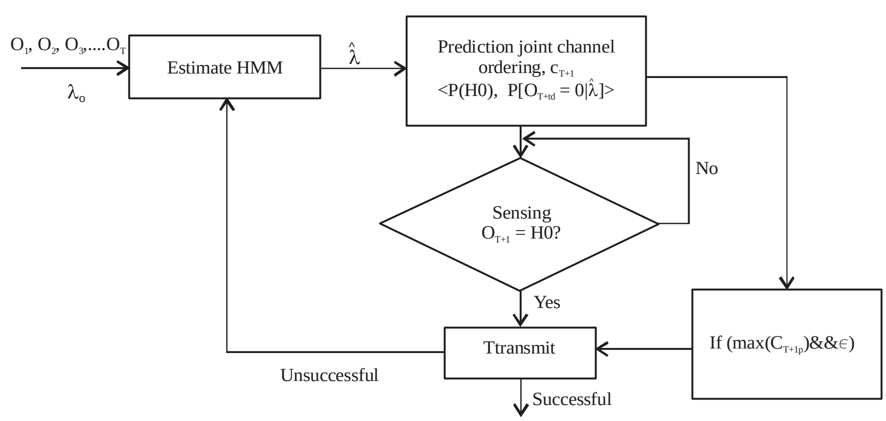

Fig. 1: Block diagram of proposed framework

Termination:

$$P\left(O_{T+1} \mid \lambda\right) = \max\left[\sum\nolimits_{i=1}^{N} \varphi_T(i) b_j(O_{T+1})\right] \quad (8)$$

The channel state of future timeslot is determined by:

$$Y(T+1) = \begin{cases} 0 & P[O_{T+1} = 1 \mid \lambda] > P[O_{T+1} = 0 \mid \lambda] \\ 1 & P[O_{T+1} = 0 \mid \lambda] \geq P[O_{T+1} = 1 \mid \lambda] \end{cases} \quad (9)$$

In this study, where channel state prediction is used, we take the opportunity to generate the potential channels sequence, $c_{T+1,p}$, for access in an optimal order. Hence, the channel with the highest probability of being available in the next timeslot joint with the longest idle period will be sensed first. Be reminded that, SU is still required to perform sensing before access to assure prediction accuracy and protect PU transmission. The remaining channels predicted idle is then arranged in order of decreasing probability for backup channels. Being said by Wu *et al.*[6], the PU spectrum occupancy states change slowly in time and the sensing results may have a strong correlation among successive sensing periods. Due to that, in our novel work, we had taken the previous SU successful transmission, ϵ from previous timeslot into our criteria for channel selection. Channel sensing for this channel, $c_{T+1,p}$ is omitted if the likelihood probability of being idle is the highest among all channels available. It had assumed that misdetection occurs in the sensing process at that channel. Hence, SU is allowed to resume transmission without hesitant. This had shown to help improve the successful of finding an idle channel quickly.

RESULTS ANS DISCUSSION

To evaluate our model, we simulate the system using MATLAB. There are 20 licensed channels in one cell for secondary use with 1MHz bandwidth each. The PU activities of each spectrum band, α and β are uniformly distributed ranges over (0.1, 0.9). The observation data is recorded from 600 recent timeslots and simulation is done over 10000 timeslots. During the sensing of PUs, we define the threshold, γ, for energy detection as described in Liang and Zeng[13]:

$$\gamma = \frac{Q^{-1}(P_f)}{\tau} + 1 \quad (10)$$

where, $Q^{-1}(\bullet)$ is the inverse $Q(\bullet)$ which is the complimentary distribution function of standard Gaussian:

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{t^2}{2}\right) dt \quad (11)$$

Meanwhile, Pf is the probability of false alarm, define as the probability of error detecting an idle channel but in actual the channel is not[13]. Let be the number of sensing samples at each sensing period. In each channel, we consider the status on/off based on the exponential distribution probability. In the simulation, we assumed the SNR of received PU signal is constantly -20 dB. The traditional random selection scheme in spectrum sensing and access is simulated to compare with our model. In our experiment, it is showed that the impact of the number of available channels on the performance of our proposed framework in terms of channel successful utilization, PU collision, number of handoff and delay of finding idle channels.

It is concluded that our framework proven to perform much better than the traditional random sensing and access in cognitive radio. The learning and prediction based on our scheme had shown its prediction accuracy and higher chance of finding channel opportunity.

In Fig. 2, it is shown that SU had increased their successful channel utilization. This proved that the channel occupancy prediction method had help in finding the correct idle channel. Figure 2 also showed that our scheme able to increase tremendously the SU transmission throughput that assured the efficiency of channel utilization. Major improvement in successful utilization is when the channel available is from 1-5 channels. However, with more channels in the cell, the performance saturated. This is due to the fact that our scenario only considered one SU to use only 1 channel. Thus, this will be beneficial for a scenario where a single or more SUs are allow transmitting using one or more channels at once to transmit its packet data.

In Fig. 3, we observed that the proposed scheme can efficiently avoid PU collision compared to the traditional channel selection. The imperfect in spectrum sensing had caused errors in PU detection. Therefore, PU collision occurred. The propose scheme had successfully minimized sensing errors where SU only sense the channel that predicted idle in the next timeslot window of length td.

The issue in traditional spectrum sensing and access is the delay that occurs to find the channel for SU occupancy. The channels are sensed one by one randomly until it finds an

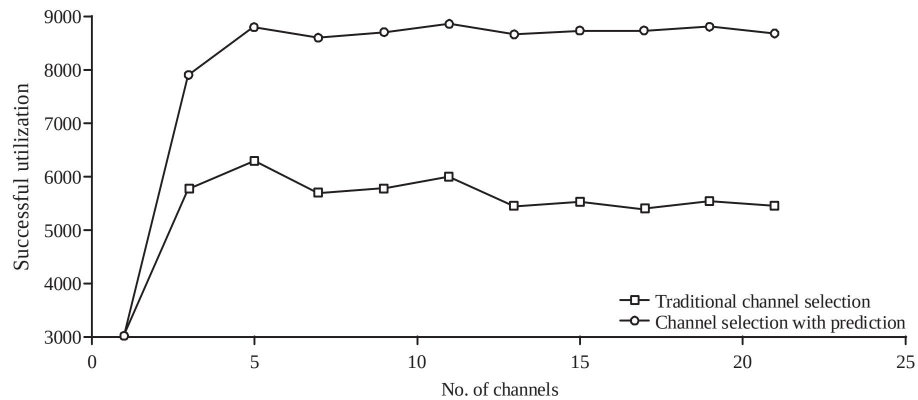

Fig. 2: Successful channel utilization

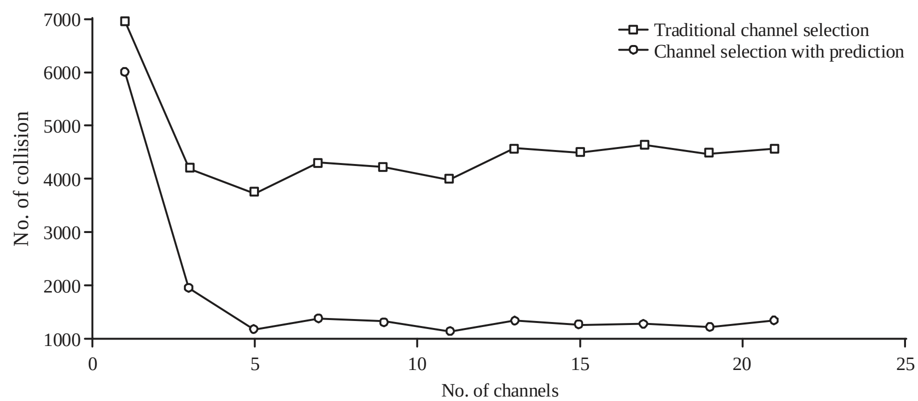

Fig. 3: Number of PU collision

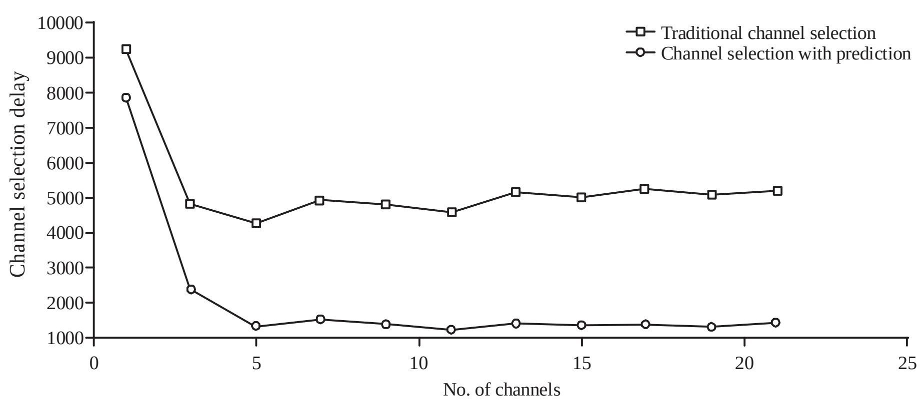

Fig. 4: Delays in finding idle channel

idle channel. This method had shown that it can save the total operation time as it can get the target channel status in advance with higher accuracy as in Fig. 4. Our proposed scheme is to reduce the number of spectrum handoff. Figure 5 illustrates the number of handoff for the secondary network. Again, it proved that with this proposed framework, the number of handoff was reduced from random selection. Note that as shown in the simulation, five channels were already sufficient for an SU to reach its highest performance if using this scheme. Hence, it will be interesting to discover the performance if it conditioned many SUs to transmit in multichannel in a cell using this method.

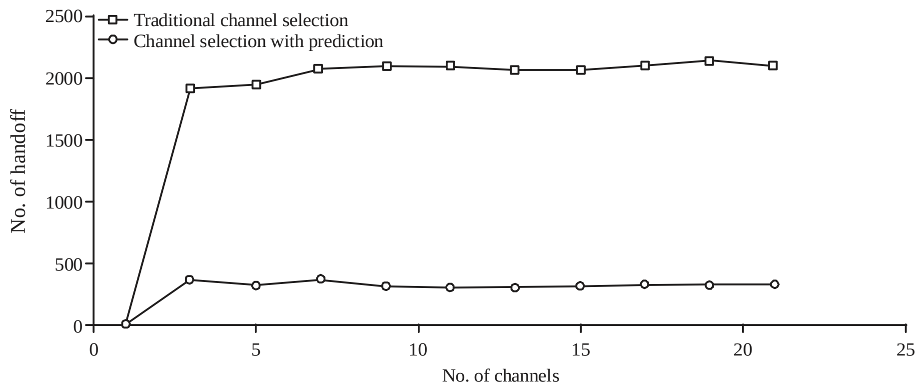

Fig. 5: Number of handoff

CONCLUSION

The main objective of this study is to utilize the spectrum efficiently according to spectrum usage patterns in CRNs. In order to analyze the proposed framework and prove its performance, we both implemented and simulated the method in MATLAB environment. The results of simulation showed that the proposed intelligent spectrum selection and access method reduced the number of delay and handoffs in CR network. This approach also improved the performance of the spectrum utilization and reduced the number of PU collision, which proved the accuracy of the prediction method used. However, there are still many outstanding issues to study. As mentioned before, with five channels an SU capable to reach its highest performance. Hence, our future works will be to analyze the impact of number of channels if there are several SUs transmit in multichannel simultaneously using this method.

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