Opportunistic Channel Selection in Cognitive Radio Networks using Moving Average Prediction

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Abstract - *In Cognitive Radio Network (CRN), effective channel utilization is imperative for secondary users to utilize network resources and improve spectrum utilization. In this direction, sensing the spectrum is a key concept to identify the availability of the primary user in the wireless channel. The secondary user can access the available wireless channels for their data transmission. But the secondary user must reposition their place to another channel when a primary user tries to access the licensed channels. This can be lessened through the spectrum prediction technique. Efficient spectrum prediction is recognized by identifying the future idle time of primary user activity in CRN. In this paper, we predict the spectrum with the help of Moving average based prediction techniques. This technique continuously senses the channel and predicts the activities of the primary user. So the utilization of the spectrum can be improved by using spectrum prediction. The prediction is measured in terms of energy based prediction, exponential moving average based prediction, order-k moving average prediction and weighted moving average based prediction.*

Key Words: Channel selection, Moving average prediction, Spectrum sensing, Spectrum prediction, Spectrum allocation

1. INTRODUCTION

Recently, the need for spectrum is increased significantly because of the increase in spectrum usage. Due to the problem of this spectrum scarcity, the FCC (Federal Communications Commission) has allowed the unauthorised users make use of the available spectrum in the absence of primary users. Assigning the spectrum for each user is not possible so it assigned over a given period. But in this static spectrum assignment policy, some portions of the spectrum are temporally vacant, this is called spectrum hole. Cognitive Radio (CR) produce an intelligence to utilize the idle spectrum opportunistically. To successfully implement the CR concept, it needs to implement the subsequent four functions; spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.

A secondary user regularly monitors the presence of a primary user then only it can efficiently utilize the available bandwidth. Because the bandwidth is vacant for a restricted time. Within that, the secondary user opportunistically uses the spectrum and improves the performance of spectrum utilization. During this spectrum sensing, the channel switching will reduce the transmit power and communication drop of a secondary user. Therefore, we propose spectrum prediction for CRN. In spectrum sensing process, a CR user can avoid some channels which are predicted as busy. So we can reduce sensing time and energy consumption. Based on the outcome of spectrum decision a CR user can select the best channel those have the maximum idle probability. This will lead to improve the usage of dynamic spectrum access. In real time, various types of prediction strategies are available. These are based on the binary form of past spectrum occupancy information and the statistical behaviour of the primary user activities. In this paper, moving average based prediction approach has been proposed for predicting the spectrum. Moving Average (MA) models predict the spectral opportunities for CRN in a specified spectrum band based on the time series. It considers that the value of the stationary series moves around the average. At the same time, we introduce a variety of moving average based prediction techniques for channel selection. It analysis the future status of the channels. Based on that, a secondary user can access the future locations of the available channels. This will improve the accessing time of the secondary user on predicted channels and increase the spectrum utilization.

2. RELATED WORKS

Annapurna K. et al. [1] has explored spectrum prediction using a neural network to improve the spectrum utilization of a secondary user. The prediction is measured in terms of mean square error and regression. Based on this the secondary user finds the less occupancy of the primary user. Anirudh Agarwal et al. [2] has designed a model to identify the activities of the primary user prediction in cognitive radio networks. They combined four machine learning algorithms, two from the artificial neural network and two from the support vector machine. The simulation results illustrate the linear SVM has performed well. Forward Backward Auto regressive spectrum prediction scheme has proposed in [3]. This method outperforms the neural network prediction accuracy listed in existing papers. A comparative study of AR, MA and ARMA predictive models are presented in [4]. These models are evaluated under two scenarios and six evaluation metrics. Ismail Butun et al. [5] have introduced mobility of prediction techniques that enhance the reliability, bandwidth efficiency and the scalability of the CRN.

A Bayesian approach is defined in [6] to predict the spectrum occupancy status and associated with an exponential weighted moving average based approach with regard to prediction probability and spectrum decision. Jiianwei Wu and Yanling Li [7] has analyzed and compared three kinds of prediction models. They summarized about the practical application, development situation and existent problems of the three forecasting methods. The call arrival rate and call holding rate of a primary user have presented in [8]. Based on that they evaluated the probability of channel availability in cognitive radio networks.

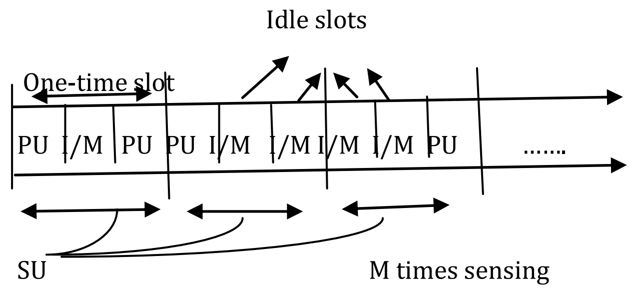
Cooperative spectrum sensing based censored energy detection followed on two witness fusion rule has suggested in [9]. These rules are used to derive the spectrum sensing final decision. They defined closed forms of the detection probability, false alarm and missed detection. The performance of this proposed scheme is analytically proved. The hybrid optimization has proposed in [10], they implement the genetic algorithm and particle swarm optimization along with the backpropagation neural network to predict the spectrum patterns in a cognitive radio network. Sweta Jain and Apurva Goel in [11] have presented a survey of various spectrum prediction techniques. They analyzed the functionality of each technique and discuss the benefits as well as drawbacks of each technique. Tumuluru et al. [12] have designed a three step spectrum prediction framework based on a neural network. They evaluate the performance of the backpropagation neural network predictor. They showed the performance of the proposed framework is very effective in terms of spectrum prediction accuracy. Vamsi Krishna Tumuluru et al. [13] has considered a channel status predictor with machine learning and hidden Markov model. Both techniques are analyzed and compared using various simulations. Xiaoshuang Xing et al. [14] have analyzed the necessity of spectrum prediction and also explained various types of prediction techniques.

Xiaobotan et al. [15] have employed time series prediction for the prediction of future busy probabilities in the licensed channel. Switching probability, throughput and collision probability has compared with random channel selection method. The exponential moving average based energy prediction method has proposed in [16] to predict the energy level of frequency bands. The secondary user skips the channels which have the highest energy than the present threshold. To the best of our knowledge, the above kinds of literature are discussed about machine learning based prediction, Markov model based prediction and AR model based prediction. In this paper, based on the spectrum occupancy past observations the moving average prediction methods are proposed. The performance of each prediction technique is evaluated in this paper.

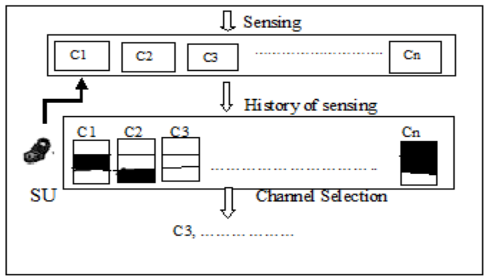
3. SYSTEM MODEL

3.1 Secondary User Model

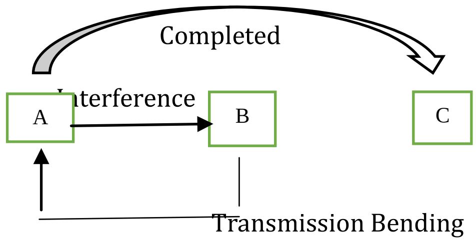
In a wireless environment, the frequency spectrum is distributed into many spectrum bands and each band is divided into several spectrum units. To achieve the idle probabilities of the spectrum unit in each time slot, the secondary users must sense the spectrum M times. If I idle states of the spectrum are detected, then the probability of the idle spectrum is defined as $\frac{I}{M}$ and shown in fig.1(a). Depends on the history of busy and idle probability the secondary user selects the channel which has the highest idle probability which is depicted in fig. 1(b).



(a) Spectrum sensing mechanism



(b) Channel selection by secondary user



(c) Data transmission flow chart

Fig.1. System model

The data transmission process is demonstrated in Fig. 1(c). We divide the channel selection process into three states. If the secondary user chooses the channel for data transmission, then it is in state A. During data transmission, if the secondary user notices the existence of a primary user then interference happens. So it moves to the next state B. Suppose the secondary user completes its data transmission its move to the state C and wait for new data transmission. Otherwise, it senses the same channel and transmits data whenever the primary user is not available in the channel.

3.2 Primary User Model

Energy based prediction technique is mainly used to improve the sensing performance of a secondary user [2]. Each CR user gathers the energy level of all channels and makes it as an observation, based on that it predicts the presence of a primary user. Then the secondary user skips those channels which have the maximum energy level than the present threshold.

The primary user is identified as

$$H_0 : y_i(t) = n_i(t) \quad (1)$$

$$H_1 : y_i(t) = h_i^g x(t) + n_t(t) \quad (2)$$

where h_i^g is refers channel gain, $n_i(t)$ is the Gaussian noise of the channel and $x(t)$ is the transmitted signal which has the power E. The i^{th} channel state is denoted as

$$E_i = \frac{1}{N}\sum_{t=1}^{N} |y_i(t)|^2 < T_1 \quad :H_0^i \quad (3)$$

$$E_i = \frac{1}{N}\sum_{t=1}^{N} |y_i(t)|^2 > T_2 \quad :H_1^i \quad (4)$$

where T_1 & T_2 are the decision threshold, E_i is the estimated energy of the i^{th} channel. After that, for each secondary user, we analyze the probability of detection and false alarm probability.

$$P_d(T_1) = prob(H_0^i \mid H_0) \quad (5)$$

$$P_{fa}(T_1, \gamma_i) = prob(H_0^i \mid H_1) \quad (6)$$

where γ_i is the signal-to-noise ratio of the primary user.

Evaluating the user arrival process in wireless networks would follow Poisson distribution [14]. But in CRN the usage of licensed channels is low. So we assume t_s is the limited primary user call arrival within a time slot and N_A is the whole number of primary user arrival within t_s. So the identification of the primary user would follow a binomial distribution.

The mean E_λ of a binomial distribution is $N_A P$. So

$$P = \frac{E_\lambda}{N_A} \quad (7)$$

$$\lambda \Delta t = \frac{\lambda t}{N_A} \quad (8)$$

where λt is the number of user arrival rate, Δt is the mean value of user arrival $\Delta t = \frac{t}{N_A}$ from equ(8) and λ is the number of user arrivals per unit time.

The calculation of a primary user arrival probability in a specified time is

$$P_{pu} = \binom{N_A}{0} p^0 (1-p)^{N_A - 0}$$
$$= (1-p)^{N_A}$$
$$= (1 - \frac{\lambda t}{N_A})^{N_A} \quad (9)$$

The expected user arrival rate between the first 30-time slot is given as

$$A_t = \int_0^{29} a(t)dt \quad (10)$$

where $a(t)$ is the arrival rate of the user and it may change over time.

The period is divided into 60 time slots, so the time interval may be measured as

$$(t_n, t_{n+1}) \quad (n = 0,1,2,3,.....59)$$

Then the time duration t_d is calculated for one interval (ie) one hour.

$$t_d = t_{n+1} - t_n \quad (11)$$

Then the user arrival rate is

$$\lambda_t = \frac{\lambda_n}{t_d} \quad (t = t_n, t_{n+1}) \quad (12)$$

where λ_n is the total number of user arrivals in the time interval. The equ(10) is used to calculate the history of primary user call arrival within a time slot. But the equ(12) is used to calculate total number of call arrivals within a time in the channel [14].

In cognitive radio networks, a CR user can calculate the probability distribution of spectrum occupancy. In this paper, we predict the probability of a i^{th} spectrum occupancy by a primary user on a particular channel. At the same time t is the spectrum occupancy and it is denoted as $p_i(t)$ where $i = 1,2,3,\ldots$, $t = \{t_1, t_2, \ldots t_T\}$

$$p_i(t) = \begin{cases} 0, if \ \ spectrum \ is \ not \ occupied, or \ idle \\ 1, \quad if \ \ spectrum \ is \ occupied, or \ busy \end{cases}$$

3.3 Channel State Model

The spectrum occupancy status of a primary user is observed by using a Markov chain model is shown in fig. 2. Let assume T is the sequence of time slots. Consider 'M' be referred as busy slots and 'N' is the idle slots observed from the sensing history. 'Q' is the number of occurrences when both current and preceding states are busy and 'P' are the number of occurrences when both current and preceding states are idle. 'R' be the number of cases where the current state is busy and the preceding state is idle. 'S' be the number of cases where the current state is idle and the preceding state is busy.

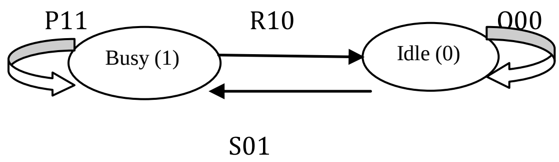


Figure 2. Channel state transition

The probability of spectrum occupancy is denoted as

$$P_{11} = \frac{Q(both\ states\ are\ busy)}{T(total\ numberof\ slots)} \quad (13)$$

$$Q_{00} = \frac{P(both\ states\ are\ idle)}{T(total\ number\ of\ slots)} \quad (14)$$

$$R_{10} = \frac{P(present\ is\ busy\ and\ previous\ is\ idle)}{T(total\ number\ of\ slots)} \quad (15)$$

$$S_{01} = \frac{P(present\ is\ idle\ and\ previous\ is\ busy)}{T(total\ number\ of\ slots)} \quad (16)$$

The above equations are used to identify the activity of a primary user on an individual channel. In addition to this, we have to calculate how much time the primary user present in each slot. Based on that, the idle time of each slot is easily identified. While accessing the licensed channel, we must ensure the secondary user can spend more time in a licensed channel without switching. So predicting the spectrum for a secondary user is the most important task.

4. PREDICTION TECHNIQUES

Different approaches and models are suggested to predict the network traffic on different heterogeneous networks. Traffic models may be stationary or non-stationary. So the introduction of time series models had done for network traffic simulation and spectrum prediction [12]. In [9] multilayer perceptron based predictor is used for identifying channel status which does require the prior knowledge of licensed user systems. Based on traffic intensity, the probability of idle and busy slots is calculated and show that performance measures likely spectrum prediction improvement and sensing energy reduction. But they consider two types of secondary users. The first one selects and senses the channel randomly. Second predicts all channels based on their slot history. Moving average is a method to acquire whole idea of the movements in a dataset. It is an average of any subset of numbers. Moving averages analyze the future status of the channels. Based on this, the secondary user can identify the future availability of the channels. This will improve the accessing time of the secondary user also increase spectrum utilization. In this prediction, historical data are analyzed to recognize a pattern. Then the pattern has extended to predict the series. The assumption of the data pattern is very important because it will lead to inaccurate predictions.

Exponential Moving Averages (EMA) reduce the delay in channel prediction by the use of recent idle slots [2]. So we focus more on recent idle slots rather than a long series of idle slots. It has three steps; first, we calculate the Simple Moving Average (SMA) it considers as initial EMA. Second, the weighting multiplier is evaluated. Third, the EMA is calculated for each slot between the initial EMA value and recent idle slot using the multiplier and previous EMA value. The formula of calculating EMA is

$$\begin{aligned} &SMA : (Sum\ of\ idle\ slots / n) \\ &Multiplier : 2/(selected\ no.of\ slots + 1) \\ &EMA : \{today * multiplier\} + \{previousEMA * (1 - multiplier)\} \quad (17) \end{aligned}$$

Where n is the number of time slots, *today* is the most recent value of the time slot and *previousEMA* is the previous recent value. The assumption is made in this article is, $P = \{p_1, p_2, p_3, p_4, p_5\}$ primary users are occupying the licensed spectrum. $S = \{S_1, S_2, ..., S_{25}\}$ secondary users are trying to access the licensed spectrum. Each channel consists of 60 time slots and each slot has a limited time interval. The sensing history has taken for 10 time slots and predict the 11th time slot by using EMA is follows

$$\begin{aligned} &Time\ slot : 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad 7 \quad 8 \quad 9 \quad 10 \\ &Idle\ time : 34 \ 29 \ 40 \ 38 \ 37 \ 36 \ 31 \ 34 \ 41 \ 36 \end{aligned}$$

$SMA =$ (356/10) =35.6

$multiplier =$ (2/ (10+1)) =0.1818

EMA = (36*0.1818) +(41*0.8182) = 40 so the idle time of 11th time slot is 40%. This process is followed for all timeslots and all channels.

In order-k moving average based prediction, we consider a sequence of idle slots. It predicts the next value of the sequence as the average of the last k values in the sequence. Consider a history I is the number of slots $i_1, i_2, ...i_n$. The order-k moving average predictor estimates the value to be

$$i_{n+1} = \frac{1}{k}\sum_{j=1}^{k} i_{n-j+1} \tag{18}$$

where n is the number of idle slots in the channel, the moving average of order k is the value of k consecutive observations. Suppose if we use $k = 3$ then it focuses on the last three idle slots (i.e.) 8th ,9th and 10th time slot is considered for this 3-order calculation.

$$i_{n+1} = \frac{i_{n-2} + i_{n-1} + i_n}{3} \tag{19}$$

11th = (34+41+36)/3=37

when we predict the next slot using order $k = 5$ means 6th ,7th ,8th ,9th and 10th time slot is considered.

$$i_{n+1} = \frac{i_{n-4} + i_{n-3} + i_{n-2} + i_{n-1} + i_n}{5} \tag{20}$$

11th = (36+31+34+41+36)/5=36

Weighted Moving Average (WMA) method is a weighted average of the last n idle slots. We assign a random cost for all idle slots between 0 to 1, but more cost is assigned to recent idle slots. The calculation of WMA is multiplying the cost with each idle time and then summing the values. The formula of WMA is

$$i_{n+1} = \sum_{i=1}^{n} c_i i_i \tag{21}$$

where c refers cost of each idle time slot, i refers to the idle time of a slot and n is the number of idle slots. The calculation of idle time for 11th time slot is

$$11^{th} = (i_8 * c_1) + (i_9 * c_2) + (i_{10} * c_3)$$

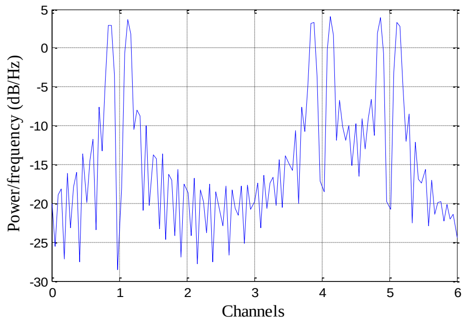
= (34*0.3) +(41*0.3) +(36*0.4)

= 36.99

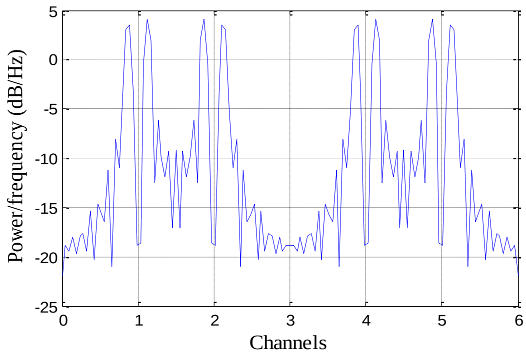
All these prediction techniques calculate the future idle time of the 11th slot based on the sensing history of 10 time slots. This process is followed for all time slots and all channels.

5. PERFORMANCE EVALUATION

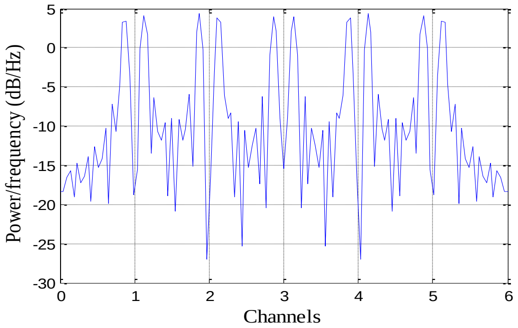
In the above sections, we explained the prediction techniques and outlined their uses in a cognitive radio network. We have simulated all the above four techniques in a Mat lab environment. Randomly, we take five channels, each channel is sensed one by one based on energy based prediction method. Then the energy value of each channel is compared to the present threshold and identifies the presence or absence of the primary user. Finally, the availability of a channel is identified which is depicted in fig. 3(a). In this figure, channels 2 and 3 are idle. So secondary users can access these idle channels easily.



(a) Channel availability



(b). Channel occupied by one user



(c). Channel occupied by all users

Fig. 3. Channel Utilization

The secondary user is randomly allocated to the 2nd channel which is explained in fig. 3(b). Now the secondary user accesses the channel till the primary user arrives on that channel. Next, another secondary user is allocated to the 3rd channel. Fig. 3(c) states the primary user and secondary user are sharing the licensed channels. The random channel selection causes the performance degradation of the secondary user. Because the secondary user must vacate the channel whenever the primary user arrives on the licensed channel. To avoid this switching, we implement spectrum prediction techniques for the secondary user. Before that, sensing the spectrum is the most important task. Here energy detection techniques are utilized to identify the presence of the primary user.

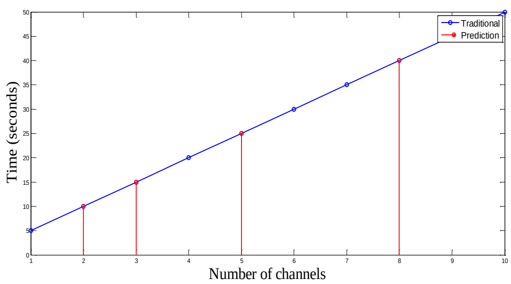


Fig. 4. Sensing time

The sensing process is compared between traditional and prediction techniques which are explained in fig. 4. The secondary user regularly senses all the channels in the traditional sensing method. If anyone of the channel is idle, the secondary user occupies the channel and begin their transmission. During this cognitive radio transmission, the secondary user must vacate the channel when the primary user arrives in that licensed channel. But in prediction, the secondary user observes the primary user activity in the past sequence of time slots then it predicts the presence of a primary user. In fig. 4, it is clear that the secondary user directly accesses 2nd,3rd,5th and 8th channels only. Because these channels have the highest idle time than other channels. So prediction techniques save 50% of the sensing time of a secondary user. For predicting the spectrum, we proposed moving average prediction techniques in this paper.

Moving average based prediction method predicts the next sequence of idle slots based on the history of previous idle slots. The secondary user senses the channel and represents the spectrum occupancy status in binary form. The state '0' signifies the channel is idle and '1' represents the channel is busy. Moving average based prediction method finds the probability of future idle slot based on the previous $'I'$ time slot, the value of $'I'$ is assigned as 60. But the calculation of actual probability can be done by creating an energy detection method. First, we proceed with the actual probability of idle time for 10 time slots. Based on that, the idle probability of the next 10 time slots is predicted with the help of moving average based techniques.

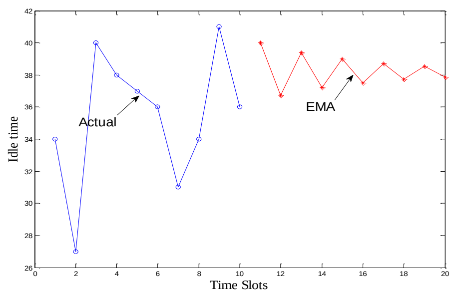


Fig. 5. Prediction with EMA

Fig. 5 illustrates the comparison between the actual probability and the predicted probability using EMA. EMA predicts the idle probability for the next 10 time slots using equ (17) is represented in the above figure. In [2], the authors combined EMA with energy detection to enhance the spectrum sensing and show that the EMA algorithm saves the sensing time significantly. But the authors compared energy based prediction techniques with EMA only. Here we compared energy based prediction techniques with EMA, WMA, and order-k moving average techniques.

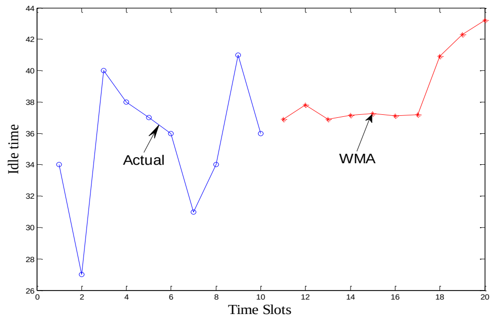


Fig. 6. Probability prediction with WMA

Fig. 6 shows the comparison between the actual probability and the predicted probability using WMA. The weight is assigned for each idle slot. Whenever the weight is increased to the most recent idle slots the idle probability is also increased. In this figure, the 18, 19 and 20th time slots have the highest idle time.

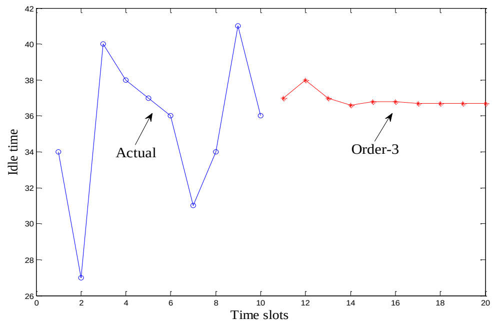


Fig. 7. Prediction with Order-3

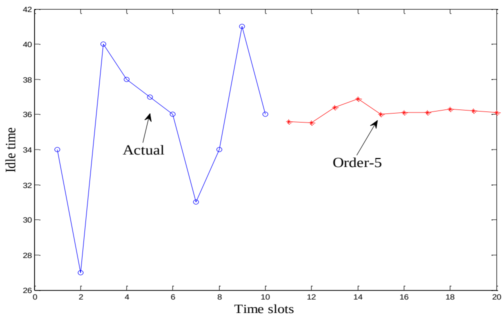


Fig. 8. Prediction with Order-5

Fig. 7 & 8 shows the performance of order-k moving average prediction techniques. Based on the k value the idle time of kth slot averaged and find the future idle time of next slot. Both techniques are performed well.

Table.1 illustrates the accuracy of two prediction techniques. In a specific channel, the accuracy is defined in the form of finding the next idle slot based on the history of previous idle slots. The WMA prediction method gives more accuracy than the other methods. In [3], prediction techniques are compared in terms of accuracy. But they implemented only the order-k moving average prediction. Here, we compared all types of moving average techniques with the traditional sensing method.

Table-1: Prediction accuracy

Method	Time	Accuracy
WMA	5s	99.4
3-order	5s	98.67
5-order	5s	98.01

Table- 2: Comparison of five techniques sensing time

Technique	No. Channels	Sensing time	Predicting time	Reduction
Traditional	1	60s	0	0
Energy	1	60s	20s	60%
EMA	1	60s	12s	76%
Order-k	1	60s	15s	70%
WMA	1	60s	13s	75.53%

Table. 2 shows that the reduction of sensing time in all five techniques. From this table, it is clear that for each channel the time reduction in sensing is increased in WMA and EMA techniques. In this paper, we consider five channels and 25 secondary users. Each energy detection takes 100ms but 50% of detection time is reduced in prediction

6. CONCLUSION

Spectrum prediction is a key mechanism that aims to avoid the performance degradation of secondary users. The research has been implemented on various types of prediction methods. In this paper, the combination of all moving average prediction techniques are put to use for predicting the spectrum. The main advantage of spectrum prediction is reducing the primary and secondary user interference and saving the energy secondary devices. Simulation results shows that the performance of EMA and WMA and both are compared to traditional spectrum sensing. Our future research involves the extensive research to be done on the long-term accurate prediction

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