Available online at www.ejournals.uofk.edu
U ofKEJ Vol. 8 Issue 2 pp. 11-17(August 2018)

UNIVERSITY of KHARTOUM ENGINEERING JOURNAL (UofKEJ)

An Improved Energy Detection Scheme Based on Channel Prediction In CR Networks

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Abstract: Cognitive radio is considered as an intelligent wireless communication system proposed to improve the utilization of the radio electromagnetic spectrum. In CR technology the secondary users take the responsibility of dynamically sensing and accessing any unused channels in the spectrum allocated to the licensed users. As spectrum sensing consumes considerable energy, predictive methods for inferring the availability of spectrum holes can reduce energy consumption of the unlicensed users to only sense those channels which are likely to be idle. It also helps to improve the spectrum utilizations. Several prediction techniques have been used to predict spectrum utilization. However, most of current approaches do not consider seasonality in spectrum workload, for example most of the channels are busy during business hours in mobile phone bands. This paper; proposes a channel status predictor based on the multiplicative seasonal model called Holt-Winters' method. The proposed prediction method has the ability to adapt with changes in trends and seasonal patterns of the sensing observations. Performance analysis and the accuracy of the channel status prediction schemes are investigated.

Keywords: *Cognitive Radio; Spectrum prediction; Channel availability; spectrum sensing.*

1. INTRODUCTION

Cognitive Radio (CR) has emerged as one of the key techniques that can help in addressing the inefficient usage of the radio spectrum, without requiring the allocation of new frequency bands by opening up the unused licensed frequencies to secondary users for opportunistic access. Spectrum utilization can be improved significantly by permitting opportunistic access to white spaces at the right place and time. For spectrum sharing-scheme and to work efficiently, it is mandatory to know the presence or absence of the primary user before exploiting spectrum opportunities. To do so, various spectrum sensing schemes [1]-[4] have been proposed so far to minimize the interference to the primary users, these schemes are: energy detection, cyclostationary detection and matched filter detection.

Each detection method has its own pros and cons. Energy detection scheme is more popular due to its simplicity and less complexity over match filtering and cyclostationary feature, it also requires less number of samples for detection. Many techniques have been proposed to enhance the performance of energy detector. For example, cooperative spectrum sensing is used to improve the detection performance [5] or adapting sensing threshold based on channel sensing information [6]. In most of these works, signal to noise ratio at secondary. Transmitter is considered to adapt sensing threshold with the assumption that it has full knowledge of channel state information (CSI). From a practical point of view, it is never possible to have full knowledge about the channel conditions as it is time varying in nature and thus keep changing with time and geographical location, so spectrum sensing module can be efficient by combining the sensing operation with a channel status prediction mechanism. The secondary user may predict the status of a channel based on the past sensing results and sense only if channel is predicted to be idle in next time slot. Thereby, the secondary user may use its sensing mechanism resourcefully.

Besides, using channel status prediction to estimate the effective bandwidth in the next slot will allow the secondary users to adjust the data rates in advance. This paper studies few methods of channel state prediction in cognitive radio wireless network and discusses their performance. It also demonstrates the advantages of channel status prediction to the spectrum sensing operation in terms of improving the spectrum utilization (SU) and saving the sensing energy and due to seasonality of channel availability, proposes a channel status predictor based on the multiplicative seasonal model called Holt-Winters' (HW) method. The rest of this paper is organized as follows: Firstly, we present an overview of spectrum prediction in CR network, then presenting Holt-

Winters seasonal based prediction. Energy Detection Scheme is shortly described. Finally, the analysis of the model scheme and results are presented then future research directions are illustrated.

2. Prediction for Cognitive Radio

In CR networks a spectrum sensing scheme uses received signals to detect channel states, and it virtually predicts channel states in the near future simply using previous detected channel states. Intensive work on prediction for cognitive radio has been reported.

Statistical methods are widely used in spectrum occupancy and spectrum availability prediction. A statistical spectrum occupancy model [7] was designed to generate accurate temporal and frequency behavior of various wireless transmission based on a combination of several probability density functions. Spectrum occupancy characterization prediction was proposed in [8] using binary time series. The performance of the predictor suffered due to the non-deterministic nature of the binary series. A neural network model multilayer perceptron (MLP) that maps sets of input data onto a set of appropriate output was used in [12], [13]. The input data is the history observations while the output is the prediction of the future states. The main challenge in MLP is the training of the model. Autoregressive model (ARM) in [16] was used to predict the status of the licensed channel; CR user first estimates the model parameters with maximum likelihood estimation or moving averages.

Then, it inputs the history observations into the prediction rule and predicts the future state of the system. This model requires knowledge of the primary user's traffic characteristics which may not be known. Moving average (MA) predictor [17] predicts the next value of the sequence as the average of the last values in the sequence. An upgrade version (exponential moving average EMA) based prediction [18], used to enhance the influence of the most recent observations on the prediction result. Bayesian theorem [14], [15] provides a method to describe the relation between the new information and updating posterior distribution. Current knowledge about the parameters is expressed by placing a probability distribution on the parameters (*prior distribution)*. When new data becomes available, it is expressed in the likelihood which is proportional to the distribution produces an updated probability distribution called the *posterior distribution*.

Markov models and hidden Markov models (HMM) are also commonly used in spectrum availability prediction. The main idea is that the latent state of the system, together with other non-observable information, are hidden as part of an observation process affected by some "noise". This hidden information is assumed to keep track of the dynamics of the finite-state Markov chain in discrete or continuous time [9], [10], and [11]. However, not all frequency channels were validated to fit the property of Markov chains and hidden Markov chains. In addition, the initial parameters needed in the Markov chain approach are hard to choose. Another limitation of first order HMM is that a state only depends on one immediate previous state.

3. Holt-Winters Seasonal Based Prediction

In cognitive radio networks, channel selection is carried out based on the history of incumbents' behavior of the channel over a period of time. Using the data recorded in the channel status table, SUs estimate the channels' status based on the multiplicative seasonal model for the next time slot.

Time-series forecasting assumes that a time series is a combination of a pattern and some random error. The goal is to separate the pattern from the error by understanding the pattern's trend, its long-term increase or decrease, and its seasonality. Several methods of time series forecasting are available such as the Moving Averages method, Linear Regression with Time, Exponential Smoothing etc. This work concentrates on the Holt-Winters Exponential Smoothing technique as applied to time series that exhibit seasonality. The Holt-Winters method is a popular and effective approach to forecasting seasonal time series. Different implementations will give different forecasts, depending on how the method is initialized and how the smoothing parameters are selected. The Holt-Winters multiplicative seasonal method [19], comprises the forecast equation and three smoothing equations one for the ***level*** (ℓt), the second for ***trend (bt)***, and the third for the ***seasonal component*** denoted by (***st)***, with smoothing parameters $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$, the number of seasons $\boldsymbol{m}$ is used to denote the period of the seasonality.

Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations. The *level* is a smoothed estimate of the value of the data at the end of each period. The trend is a smoothed estimate of average growth at the end of each period. Seasonality Index (*SI*) of a period indicates how much this period typically deviates from the annual average. At least one full season of data is required for computation of *SI [22]*.

Suppose the time series is denoted by $y_1,\ldots,y_n$ and the seasonal period is m. Let $\hat{y}_{t+h|t}$, be the *h*-step forecast made using data at time t. Then the multiplicative formulation of Holt-Winters' method is given by the following equations:
Level smoothing:

$$\ell_t = \alpha\,(y_t/s_{t-L}) + (1-\alpha)\,(\ell_{t-1}+b_{t-1}) \qquad (1)$$

Where y(t) is the observation, (ℓ_t) for level factor, S_{t-L} is the seasonal factor and $0 < \alpha < 1$ is a smoothing constant, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter (α). Dividing y_t by s_{t-L}, (*which is the seasonal factor for period T computed one season L periods ago*), deseasonalizes the data so that only the trend component and the prior value of the permanent component enter into the updating process for of the deseasonalized level ℓ_t.

Smoothing of the trend factor:

$$b_t = \beta(\ell_t - \ell_{t-1}) + (1-\beta)\, b_{t-1} \quad (2)$$

Where b_t is the trend factor and $0 < \beta < 1$ is a second smoothing constant. The estimate of the trend component is simply the smoothed difference between two successive estimates of the deseasonalized level.

Smoothing of the seasonal index:

$$\bar{s}_t = \gamma\, (y_t / (\ell_{t-1} + b_{t-1})) + (1-\gamma)\, \bar{s}_{t-L} \quad (3)$$

Where $0 < \gamma < 1$ is the third smoothing constant. The estimate of the seasonal component is a combination of the most recently observed seasonal factor given by the observations y_t divided by the deseasonalized series level estimate $\ell_{t-1,}$ trends and the previous best seasonal factor estimate for this time period.

Values of Prediction:

Assuming that the seasonal pattern is relatively constant over the time period value of Holt-Winters prediction values will be given by:

1. Prediction for the next period

$$F_t = (\bar{\ell}_{t-1} + \bar{b}_{t-1})\bar{S}_{t-1} \quad (4)$$

Note that the best estimate of the seasonal factor for this time period in the season is used, which was last updated L periods ago.

2. Multiple-step-ahead forecasts (for h) The value of forecast h periods hence is given by:

$$\hat{F}_{t+h|t} = (\ell_t + h b_t) S_{t+h-L} \quad (5)$$

$\hat{F}_{t+h|t}$ is the forecast at *h* periods ahead, *t* is an index denoting a time period. The constants α, β, and γ must be estimated in such a way that the Mean square error (MSE) of the error is minimized.

A. *Initial values of model parameters*

The *level* is obviously the average of the first season of data. For initialization the level factor will be calculated as:

$$\ell_m = (y_1 + \ldots + y_m)/m \quad (6)$$

The initial trend is given by

$$b_m = [(y_{m+1} + y_{m+2} + \ldots + y_{m+m}) - (y_1 + y_2 + \ldots + y_m)]/m^2. \quad (7)$$

The trend is set to be the average of the trends for each period in the first two seasons:

$$(Y_{m+1} - y_1)/m, \quad (y_{m+2} - y_2)/m, (y_{m+m} - y_m)/m. \quad (8)$$

Then, for multiplicative seasonality $s_i = y_i/\ell_m$, where $i=1,\ldots,m$. The initial seasonal values $s_{m+1},\ldots,s_0$ are computed from experimental subjective assessments, before any data is taken into account. Through n time-slot spectrum sensing, some observed data are collected. Then, the CR user computes a seasonal factor, as the probability of the observed data given that parameter, then SUs can estimate the channels' status based on the multiplicative seasonal model for the next time slot by fitting a moving average smoother to the first 2 or 3 seasons data then divide the smooth trend by the original data to get de-trended data. The initial seasonal values are then obtained from the averaged de-trended data. Next divide the seasonal values by the original data to get seasonally adjusted data. Fit a linear trend to the seasonally adjusted data to get the initial level ℓ_0 and the initial trend slope b_0.

B. *Stationarity*

To perform forecasting, most techniques require the stationarity conditions to be satisfied. Time series X(t) is a first order stationary if the expected value of y(t) remains same for all t , so during the formulation of the problem, the channel state transition probabilities along one time slot was assumed to be constant.

The analysis of the results obtained is based on considering the following variables: observation of channel availability or probability of detection (P_d) and error criteria analysis (root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE)).

4. Energy Detection Scheme

Spectrum sensing can be described as a method for identifying the presence of a signal in a noisy environment and can be described in its simplest form [17] as a binary hypothesis problem as,

$$\boldsymbol{H_0}: y[n] = w[n] \qquad n = 1,\ldots N \quad (9)$$

$$\boldsymbol{H_1}: y[n] = x[n] + w[n] \qquad n = 1,\ldots N$$

Where *y[n]* denotes the received signal, *x[n]* expresses the primary signal, *w[n]* is noise and *n* is the sample index. The null hypothesis, H_0, corresponds to the absence of a primary signal, whereas the alternative hypothesis, H_1, indicates the presence of a primary signal. In order for the SU to distinguish between hypotheses H_0 and H_1, a test statistic, T_x, is compared with a detection threshold, λ, as follows,

$$Tx \underset{H0}{\overset{H1}{\gtrless}} \lambda \quad (10)$$

The sensing accuracy can be evaluated using three probabilistic metrics known as the: probability of detection, (P_d); probability of missed detection, (P_{md}); and probability of false alarm, (P_{fa}). P_d expresses the rate of correct signal detections, while P_{fa} expresses the rate of incorrectly detecting a signal which is actually not present. P_{md} expresses the rate of detection failures. These metrics are expressed as conditional probabilities by:

$$P_d = P(Tx > \lambda \mid H_1) \quad (11)$$

$$Pfa = P(Tx > \lambda \mid H0) \quad (12)$$

$$P_{md} = P(Tx < \lambda \mid H1) \quad (13)$$

In Energy Detection ED-based spectrum sensing, the received signal is altered within the bandwidth of interest, squared and integrated over a given observation interval in order to measure the received signal's energy level and then compare it with a detection threshold. The received signal can be mathematically described as:

$$y(n) = x(n) + w(n) \tag{14}$$

Where $x(n)$ is the transmitted signal, $w(n)$ is the Additive White Gaussian Noise (AWGN), and n is the sample index.

For simplicity, both the noise and the signal term are modeled in Gaussian random variables with zero mean and variance σ_x^2 therefore, $x(n)=N(0,\sigma_x^2)$. Simulated value for Gaussian primary user signal was represented by:

$$x(n) = \sqrt{\text{SNR}}.\text{rand}(1,N) \tag{15}$$

Where rand(1,N) is AWGN noise, SNR is signal to noise ratio. In ED-based spectrum sensing the test statistic is obtained by the received signal's energy as,

$$TED = \sum_{n=0}^{N} |X(n)|^2 \tag{16}$$

T_{ED}, is a sum of N Gaussian random variables, the Probability Density Function (PDF) follows a chi-squared distribution. N represents the maximum number of samples. Hence, based on the Central Limit Theorem (CLT), the test statistic can be approximated by a Gaussian distribution as,

$$T_{ED} \approx \begin{cases} N(N\sigma_w^2, 2N\sigma_w^4) & ,Ho \\ N(N(\sigma_w^2+\sigma_x^2), 2N((\sigma_w^2+\sigma_x^2)^2) & ,H1 \end{cases} \tag{17}$$

The closed-form expressions for the probabilities P_{fa} and P_d over AWGN are evaluated as: [6].

$$P_{fa} = Q\left(\frac{\frac{\lambda}{\sigma_w^2} - N}{\sqrt{2N}}\right) \tag{18}$$

$$P_d = Q\left(\frac{\frac{\lambda}{\sigma_w^2+\sigma_x^2} - N}{\sqrt{2N}}\right) \tag{19}$$

Where λ is the detection threshold and the $SNR = \sigma_x^2 / \sigma_w^2$.

Q-function, the generalized Marcum is denoted by:

$$\text{Qm}(a,b) = \frac{1}{a^{m-1}} \int_b^\infty x^m \, e^{-\frac{x^2+a^2}{2}} . I_{(m-1)}(ax). dx$$

Although ED-based spectrum sensing is considered as the most popular spectrum sensing method, it has several limitations including: poor detection performance in low SNR regions; need for accurate noise variance estimation; and inability to differentiate between different types of PU signals.

The P_{fa} target values may vary depending on the application. However, P_{fa} values between 10^{-2} and 10^{-1} are considered in the literature, whereas the IEEE 802.22 standard recommends a $P_{fa} < 10^{-1}$ [21]. High P_{fa} values result in inefficient spectrum utilization and hence, an overall performance degradation. Thus, for optimal spectrum sensing, high detection probability is required, while false alarm probability must be kept as low as possible to prevent spectrum under-utilization. As a result, a pair of high Pd and low P_{fa}, indicates superior detection performance.

Spectrum sensing based on ED is obtained by plotting P_d versus P_{fa} as shown in Fig.1.

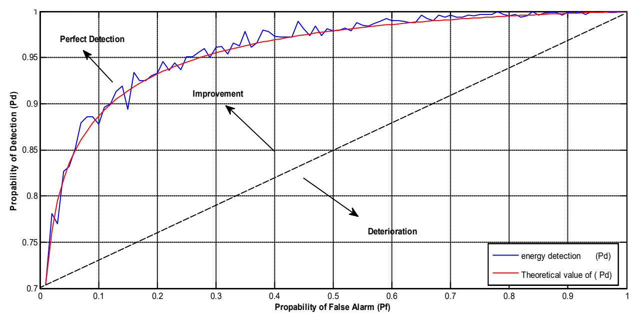

Fig. 1. Energy Detection Performance

Fig.1 describes the probability of detection of an idle channel P_d based on conventional energy detection scheme over AWGN for a range of a SNR values. The P_{di} line refers to the ideal theoretical values.

The received SNR depends on the PU transmit power and propagation environment and it can significantly affect the detection performance in terms of P_d, P_{fa} and P_{md} (equation 15). As expected, the detection performance improves as the Signal to Noise Ratio (SNR) increases. Thus, achieving a target sensing accuracy at low SNR regions suggests superior detection performance fig 2.

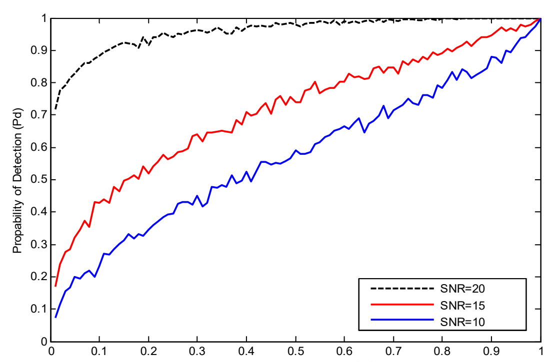

Fig. 2. ED-based Spectrum Sensing Over AWGN for Different SNR.

According to Fig 2 It is evident that the detection performance is improved as the received signal's SNR increases since the curves move towards the upper left corner of the space, it also showed the poor energy detection for low SNR that's prove the need of channel status prediction to the spectrum sensing operation in terms of improving the sensing schemes and saving the sensing energy.

5. FRAME WORK AND SIMULATION MODEL

In our framework, receiver senses through a sensing time slot with the intention of acquiring the intended level of detection quality (assuming the sensing error is negligible). The SUs are monitoring the PU activity using ED-based spectrum sensing and stores the sensing outputs in its memory. The past spectrum sensing outputs are then used as inputs into the seasonal Holt-Winters based prediction model to determine the spectrum occupancy output at future time instants as depicted in Fig.3. Upon the request of data transmission the SU senses only the channels that have been predicted to be unoccupied.

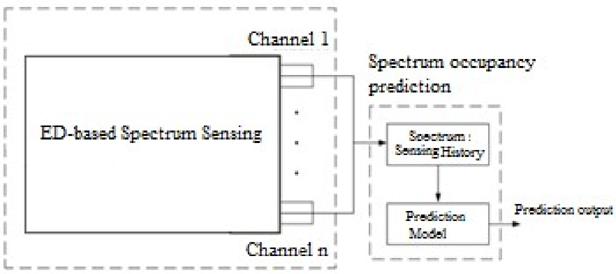

Fig.3. Frame work model

As depicted in Fig. 3, the channel occupancy in a slot can be represented as busy or idle depending on the presence or absence of a primary user activity. A time series y (t) is generated for the channel by sensing (or observing) the channel occupancy for a duration time. The time series is converted into a binary time series of 0's and 1's using three sholding. The binary symbols 1 and 0 denote the busy and idle channel status, respectively. Using the binary series, the predictor is trained to predict the primary user activity in the next slot based on past observations by obtaining the trend and seasonal factors as expressed in equation (4) and (5). Noise is modeled as AWGN with variance σ_w=1 and the corresponding noise samples are drawn from a Gaussian random process N (0, 1). In a multiple channel system, a predictor is assigned to each channel.

Simulated results are presented to validate the theoretical results of the proposed scheme. The model was simulated in MATLAB environment.

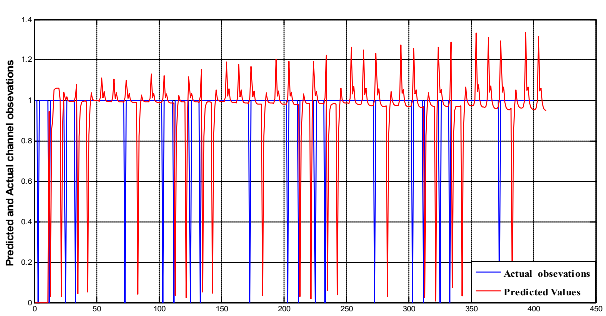

Fig. 4. Holt-Winter based prediction curve for channel occupancy

Fig 4 shows the performance comparison between random ED sensing (binary series obtained from the observations) and channel predicting occupancy based on Holt-Winters scheme. It can be seen that the Holt-Winters predictor performance follow the real history seasonal observations.

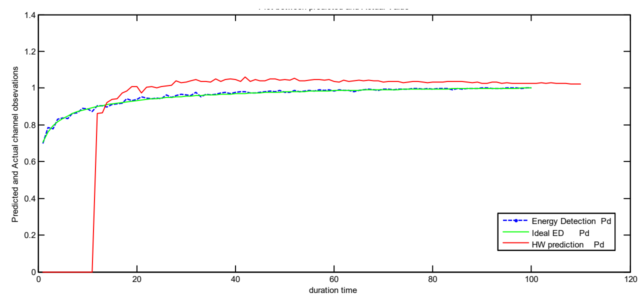

Fig. 5. Probability of Detection using HW Model

Fig.5 compares the performance of different detection probabilities, theoretical, conventional energy detection, and Holt-Winters predictor-based scheme. Holt-Winters predictor-based scheme shows higher values for probability of detection P_d than the conventional P_d and theoretical P_d under the same traffic scenario. The prediction performance is then evaluated by comparing predictor's output with the occupancy states of the test data-set. Tables I display the errors between real and predicted data of the models. This analysis included different variables to estimate errors: root mean squared error *RMSE* and mean absolute percentage error *MAPE*. *Holt-Winters' model* offers low error values.

Table1. Errors among the forecasted models for channel occupancy

MAPE	RMSE
0.007817	0.000542

6. ED-PREDICTION PERFORMANCE IMPROVEMENT

Performance for prediction schemes in spectrum sensing is evaluated using two performance measures, percentage improvement in spectrum utilization and percentage reduction in sensing energy.

C. *Improvement in Spectrum Utilization*

Consider network with each secondary user (CR) is able to sense only one channel during a slot due to the hardware constraint then every secondary user stores a short history of the sensing results for every channel, this information can be collected from neighbors over a common control channel. Considering two types of secondary users, one device randomly selects a channel at every slot and senses the status of that channel, while the other one individually predicts the status of all channels based on their respective slot history, before sensing, both devices use the same sensing mechanism and have the same level of sensing accuracy. The channel to be sensed by the CR-predict device is randomly selected among those channels with idle predicted status. SU's spectrum utilization can be defined as the ratio of the number of idle slots discovered by the secondary user to the total number of idle slots available in the system over a finite period of time (e.g.10K slots).

$$SU_{utiliz}=\frac{Number\ of\ idle\ slots\ sensed}{Total\ number\ of\ idle\ slots\ in\ a\ \text{period of time}} \qquad (20)$$

The percentage improvement in channel utilization due to channel status prediction can be expressed as:

$$Imp\ (\%) = (\text{Idle}_{\text{predict}} - \text{Idle}_{\text{sense}}) \times 100 \qquad (21)$$

Where Idle_sense and Idle_predict, represent the number of idle slots sensed by the CR-sense and the CR-predict devices, respectively. Table II shows that a CR predict device using Holt-Winter predictors can discover more idle slots than a CRsense device. The percentage of improvement in SU is more than 82% when the CR predicts device uses Holt Winter's predictor.

Table II shows that a CR predict device using HW predictors can discover more idle slots than a CR sense device. The percentage of improvement in SU is more than 82.5% when the CR predicts device uses Holt Winters predictor.

Table 2. Performance improvement in sensing

ED Idle_sense	HW Idle_predict	HW Imp (%)
92.415	175	82.500000

D. *Reduction in Sensing Energy*

CR sense device senses all the slots whereas a CR predicts device only senses when the channel status of the slot is predicted to be idle. In other words, when the slot status is predicted to be busy, the sensing operation is not performed, thereby sensing energy is saved. We assume both device types use the same sensing mechanism and have the same level of sensing accuracy. If we assume one unit of sensing energy is required to sense one slot, then the total sensing energy required for a CR sense device in a finite duration of time (e.g., 10 000 slots) can be given by:

$$\text{SEsense} = (\text{total No of slots in duration}) \times (\text{unit sense energy}) \qquad (22)$$

While the total sensing energy required by the CR predict device can be given by:

$$\text{SEpredict} = (\text{SEsense} - (\text{Busypredict})) \times (\text{unit sensing energy}) \qquad (23)$$

Where Busypredict is the total number of busy slots predicted by the CR predict device. Therefore, the percentage reduction in the sensing energy can be given by:

$$\text{SEred}(\%) = \frac{\text{SEsense} - \text{SEpredict}}{\text{SEsense}} = \frac{Busypredict}{Total\ number\ of\ slots} \qquad (24)$$

Table III shows the percentage of reduction in the sensing energy when CR predict devices with HW predictor and, It can be seen that, more busy slots are predicted and hence more sensing energy is saved.

Table 3. Sensing Energy Reduction

SE Total No of slots	**Predicted SE**	**Reduction in SE**
10000	173.0	82.7 (%)

When predictive spectrum sensing is employed, the CR senses only the channels that will be predicted to be unoccupied. Hence, for predictive spectrum sensing the number of sensed

Channels equals to the number of the predicted channels, $Nsense = Npredict$, with $Npredict \leq Ntotal$. Therefore, predictive spectrum sensing is expected to reduce the sensing cost in terms of the required sensing energy and time. The percentage of saved sensing cost compared to the conventional ED-spectrum sensing is obtained as,

$$\text{Cost}_{\text{Sensing}} = \frac{\text{N}_{\text{total}} - \text{N}_{\text{predict}}}{\text{N}_{\text{total}}} \qquad (25)$$

Predictive spectrum sensing can obviously reduce the sensing cost compared with conventional ED-based spectrum sensing.

CONCLUSION

Since, wireless channel in Cognitive Radio networks is time varying in nature, it is extremely difficult to estimate it accurately through the conventional detection scheme with fixed threshold. Therefore channel selection process employed by SUs in a CR network should benefit from improved methods to correctly and quickly perform channel allocations. This may lead to a reduction in the number of unnecessary channel switches to be performed. This will increase SU data throughput, reduce the amount of interference experienced by PUs due to SU activity and reduce the energy used for sensing the channels. This research validates predictive methods for the availability of channels. This approach allows CR terminals to sense only the channels that are predicted to be unoccupied rather than the whole band of interest. Based on this approach, a spectrum occupancy predictor is developed and experimentally validated.

The proposed scheme achieves a prediction accuracy of up to 93% which in turn can lead to up to 84% reduction of the spectrum sensing cost. The proposed model aims to improve upon existing channel prediction methods by focusing on providing better prediction accuracy, quicker solution convergence times and lower computational complexity. A spectrum sensing scheme uses received signals to detect channel states, and it virtually predicts channel states in the near future simply by using previous detected channel states. Our future research involves further extensive empirical investigations and analytical studies on the proposed approach.

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