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A Survey of Spectrum Prediction Techniques for Cognitive Radio Networks

Sweta Jain and Apurva Goel

Department of Computer Science and Engineering
Maulana Azad National Institute of Technology
Bhopal, India.

Abstract

Cognitive radio networks provide an opportunity for unlicensed users (secondary users) to use the allocated spectrum band when not in use by legitimate users (primary users). To use a channel or spectrum, it is required to sense the channel for the presence of primary user which is called Spectrum Sensing. In order to reduce the sensing time of spectrum and to determine the state of the channel whether it is free or not in advance, spectrum prediction techniques can be used. In this paper, different techniques and learning models that can be applied to predict the state of spectrum band for the presence of primary user are discussed.

Keywords: Cognitive Radio Networks, spectrum prediction, channel state prediction, activity modelling

INTRODUCTION

With the increase in number of users, the need of spectrum has also increased significantly. However, the spectrum band or bandwidth available for the communication is limited. Federal Communications Commission (FCC) in US is one of the main central authorities that allocate and regulate the spectrum bandwidth. The FCC frequency chart [1] shows the spectrum allocated over all the frequency bands. This chart explains the spectrum scarcity especially for the band under 3GHz. On the contrary, actual measurements that were taken in downtown Berkeley as shown in Figure 1 [2] reveals a distinctive utilization of 0.5% in 3-4 GHz frequency band which further drops to 0.3% in the 4-5 GHz band. This suggests that the spectrum available for communication is mostly allocated but it is often used inefficiently. To deal with the problem of spectrum scarcity and inefficient spectrum usage, FCC has permitted the unlicensed users to use the spectrum in the absence of licensed users. This provides a way to various technologies such as dynamic spectrum access, cognitive radio networks, software defined radios etc. Cognitive Radio Networks can be primarily used for this purpose due to their ability to adapt to networks conditions. According to Thomas et. al. [4] "*A cognitive network is a network with a cognitive process that can perceive current network conditions, and then plan, decide, and act according to those conditions. The network can learn from these adaptations and use them to make its future decisions, while taking into account the end-to-end goals"*. Cognitive radio networks enables the unlicensed users often termed as secondary users to use the available channel bandwidth in the absence of licensed user or primary user. Since secondary users can use the spectrum band only in the absence of primary user, on the appearance of primary user appears they have to evacuate the band immediately. Thus to use a spectrum band, secondary users have a limited time period in which it has to select the appropriate band, transfer the data and evacuate the band. The major spectrum management functions are: spectrum sensing, spectrum decision, spectrum sharing and spectrum mobility [3].

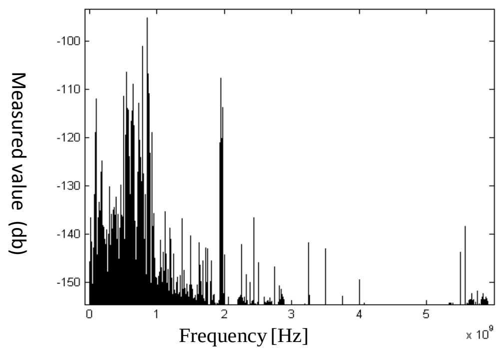

Figure 1. Measurement of Spectrum utilization at BWRC[2]

In order to use the available bandwidth, secondary users have to sense the spectrum for the presence of primary user, so that CR users or secondary users can dynamically use the available bandwidth. But the bandwidth is available only for a limited time period. Thus to save the spectrum sensing time and increase the efficiency of spectrum utilisation, spectrum prediction or channel state prediction techniques can be used. By using channel state prediction techniques, CR user can skip sensing those channels which are predicted to be busy, hence saving the sensing time as well as energy. Figure 2 shows the trade off between spectrum sensing time and spectrum access time. Spectrum prediction techniques can also be used to determine the quality of service provided by the channel. A number of techniques have been introduced over a period of time to predict the channel state. Considerable amount of research is going on in this direction to provide more accurate predictions. In this paper, we discuss different methods and the research that has been done so far on the techniques that have been used for the channel state prediction.

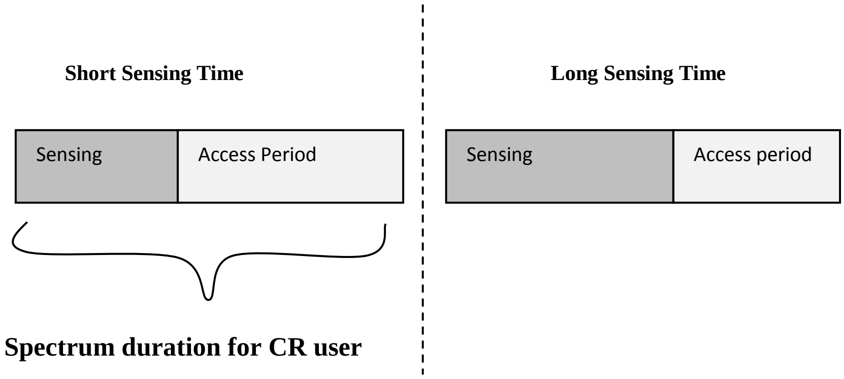

Figure 2. Trade-off between Spectrum Sensing Time and Access Time

Rest of the paper is organized as follows: Section 2 presents a brief discussion on the different functions performed in cognitive radio networks, Section 3 reviews the different spectrum prediction techniques and their applications followed by a conclusion in section 4.

FUNCTIONS PERFORMED BY COGNITIVE RADIO NETWORKS

Cognitive radio networks consist of two types of users, primary users and secondary users. Primary users are the licensed users that are allocated the spectrum. Secondary users are CR users which use the available bandwidth or spectrum when primary users are not using it. If a primary user appears while secondary user is in the middle of communication, secondary users have to evacuate the spectrum and look for another channel to continue its communication. Figure 3 shows the different activities performed by CR users [5].

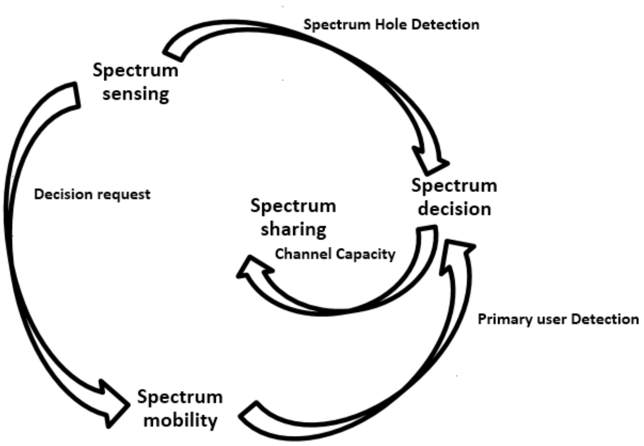

Figure 3. Activities performed by CR users

a) Spectrum sensing

Spectrum sensing is one of the major functions of CR networks. Secondary users can use only the unused portion of the spectrum which requires monitoring of the spectrum and detection of the spectrum holes. The basic functions performed during spectrum sensing are:

1. Sensing control: Sensing control enables the CR users to adapt themselves to the network conditions. Figure 4 shows two main issues of sensing controller: a) in-band sensing- for how much time and how frequently spectrum should be sensed to achieve sufficient sensing accuracy and b) out-of-band sensing i.e. how quickly CR user can find the spectrum hole.

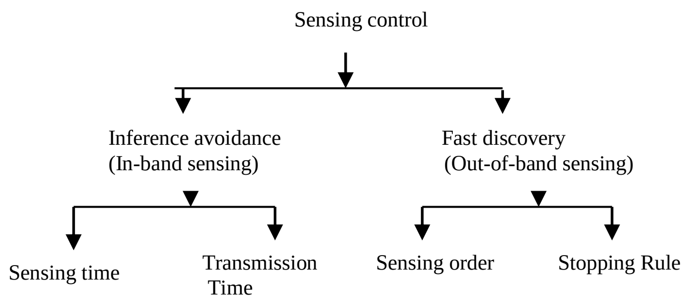

Figure 4. Sensing Control

2. PU detection: CR user monitors the environment for the presence of primary users and identifies the spectrum holes.
3. Coordination: In cooperative sensing gathered information is shared with other secondary users.

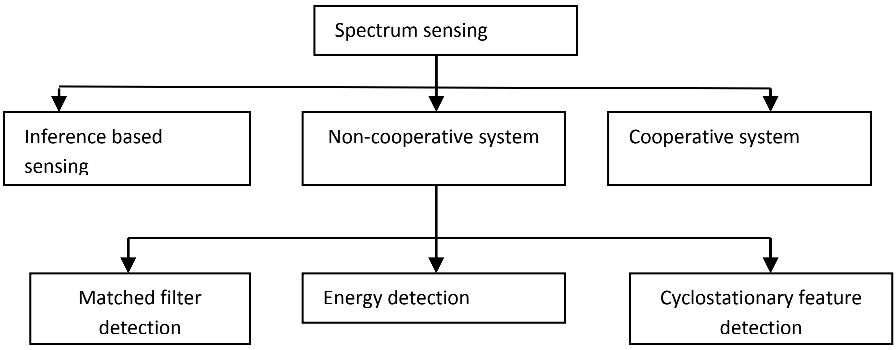

Figure 5. Spectrum sensing

b) Spectrum decision

Spectrum decision is the capability of the secondary user to decide the best spectrum available according to the quality of service required by the application from the pool of available channels. It involves spectrum selection, spectrum characterization and CR reconfiguration function.

After vacant channels are identified using Spectrum sensing, geo-location database or some other technique, each channel is characterized on the basis of statistical information and local observations. Based on this information most appropriate channel is selected. Then a CR user should be capable to reconfigure its transceiver parameters to support communication.

1. Spectrum characterization: Secondary users characterize the spectrum bands on the basis of interference, strength of received signal and the number of users currently residing in the channel.
2. Spectrum selection: It includes spectrum selection in centralized CR networks and distributed CR Networks.

c) Spectrum sharing

The main challenge after detecting the available spectrum is sharing the spectrum among CR users. Spectrum sharing is the distribution of spectrum among the secondary users according to the requirements and cost of usage.

Spectrum sharing can be classified according to three main aspects [6]:

1. Architecture: This spectrum sharing technique assumes that the spectrum access in Cognitive Radio networks can be distributed or centralized. In central spectrum sharing technique the spectrum allocation measurements are forwarded to a centralized entity that constructs an allocation map. Spectrum allocation and access is controlled by the centralized entity. While in distributed spectrum sharing, no central authority is present. Each node or user allocates and access the spectrum based on local measurements.
2. Behaviour of spectrum allocation: Spectrum can be accessed in a cooperative behaviour or a non-cooperative behaviour. Cooperative or collaborative spectrum sharing considers the effect of communication of node on other nodes. On the other hand, non-cooperative spectrum sensing considers only the node in hand.
3. Spectrum access technique: There are basically two types of access techniques overlay and underlay spectrum sharing. In overlay spectrum access method, a secondary user accesses the network via those channels which are currently not in use of primary users, thus creating minimum interference. Whereas in underlay spectrum access method, secondary users access the network by observing spread spectrum technique.CR user interferes with primary user at certain points in underlay method.

d) Spectrum mobility

If a channel currently in use by secondary user is required by the primary user, secondary user have to leave the channel and communication have to be continued in another vacant channel. This is called spectrum mobility which leads to spectrum handoff. Spectrum mobility has mainly two functionalities spectrum handoff and connection management. Handoff in cognitive radio networks can be due to different reasons; a) primary user is detected, b) secondary user lost its connection due to mobility c) channel in use cannot meet the QoS requirements. Spectrum handoff mechanisms for selecting the target channel to continue the communication can be of two types:

Proactive spectrum handoff, where secondary users select their target channel before starting the transmission and perform handoff when any undesirable situation occurs. In proactive spectrum handoff spectrum switching is faster but it requires complex algorithms since it maintains its current transmission and search for the new band concurrently. It is mostly suitable for spectrum quality degradation and user mobility.

On the other hand, in reactive spectrum handoff, target channel is not selected in advance rather it is selected when link failure occurs. Spectrum mobility is performed on an immediate basis without any preparation time. There is a significant degradation in quality of ongoing transmission, but the algorithm is less complex. It is generally used when a primary user appears in the spectrum in use.

SPECTRUM PREDICTION TECHNIQUES AND THEIR APPLICATIONS

Spectrum prediction is a challenging problem in cognitive radio networks that involves Primary user activity prediction, channel state prediction, transmission rate prediction and radio environment prediction. Spectrum prediction is supposed to add an additional layer of pro-activeness to CR functions. It can provide reduced sensing time, provide robust and flexible channel selection and establish proactive handover strategy to avoid collision with licensed user. In this section various channel prediction methods and their applications are discussed in detail. Spectrum prediction reduces the spectrum sensing time and improves the bandwidth efficiency, reliability and scalability.

a) Prediction based on Bayesian Inference

Bayesian Inference is a method of statistical inference which uses Bayes' theorem. The probability for a hypothesis is updated by using Bayes' theorem as more data becomes available. In [7], a channel quality prediction scheme is proposed. Spectrum sensing process is modelled as the Non-stationary Hidden Markov Model (NSHMM) and model parameters are estimated through Bayesian Inference using Gibbs sampling. Channel status is modelled using NSHMM and a channel quality evaluation scheme is proposed so that the secondary user can select a channel with high quality. This scheme also considers the preference of secondary user. After the process each channel is associated with a predicted channel quality and the channels are ranked. Hence ordered sequence can be used for both spectrum sensing and spectrum decision.

b) Prediction based on Hidden Markov model

Hidden Markov model is a statistical model for modelling generative sequences and it can be regarded as an underlying process that generates an observable sequence. HMM can be used for analyzing and modelling sequential data or time series in any field. The system to be modelled is considered as Markov process with hidden states.

In [8], a Markov-based channel based prediction algorithm (MCPA) has been proposed for dynamic spectrum allocation. Channel occupancy state i.e. channel is busy or idle is hidden in cognitive radio networks since they cannot be observed directly. The observation of channel states are sensing results of secondary users. By using spectrum usage pattern, different HMMs first train themselves and then spectrum manager decides which channel to use based on the likelihood of spectrum holes in these channel bands. Spectrum usage patterns are assigned binary number where 0 represents the spectrum being idle and 1 represents that the channel is in use by the primary user. These binary vectors are training sequences for different HMMs which then predict the occurrence of spectrum holes. To obtain the parameters of HMMs, the forward-only BWA is used. The spectrum usage statistics are assumed to be Poisson Distributed. The major limitation of this work is that it assumes only presence of single primary user only.

In [9], in order to minimize the negative impact of response delays caused by the hardware platforms, HMM based channel state prediction is proposed. Time delays are introduced during spectrum sensing that reduce the accuracy of sensing. Hence transmission collision can occur between the primary and secondary user due to inaccurate spectrum sensing in real time. Spectrum decision based on channel state prediction can provide an effective way to overcome this situation as the secondary users obtain the results from both spectrum prediction and spectrum sensing. Spectrum utilization efficiency can be improved by selecting a channel that is predicted as well as sensed to be idle.

In [10], spectrum sensing (SS) slots and spectrum sensing and data transmission (SSDT latency) is taken into consideration. This paper proposes prediction based on high-order HMM to compensate the SSDT latency in spectrum sensing. Statistical methods are used to calculate the parameters of high-order HMM. During sensing received signals are transformed to frequency domain by using fast Fourier transform (FFT). Numerous frequency points within one frequency band are then quantified and fed to high-order HMM as the observed value. The output is predicted state of channels for sensing slots. It also predicts the likelihood probabilities for each of the state possible. High order generalizes first order HMM by extending the dependency from one previous state to R states, as in first order HMM state depends on only one previous immediate state. As the number of states R increase, the complexity of proposed algorithm also increases, so another algorithm called AA-HMM is also proposed which is derived from Viterbi algorithm for first-order HMM.

c) Prediction based on Artificial Neural Networks

Artificial neural networks (ANN) are identical to biological cells of human brain which consist of a number of interconnected processors known as neurons. The Architecture of ANN consists of a number of neurons and links connected to them into different layers. Different learning algorithms are used to train a ANN model that depends on the desired output and the type of neural network being used. Weights are updated during the training phase using the learning algorithms. ANN can be very useful for prediction when we have a very little knowledge of the network as in case of cognitive radio networks. Various ANN have been used over the time to predict the spectrum. Some of them are discussed here.

In [15], a Multilayered Feed forward Neural Networks (MFNN) has been proposed for modelling the performance of Cognitive Radio functions. CR radio networks can effectively learn using MFNN even if the number of inputs and outputs are high. MFNN is trained by Back-propagation algorithm by making use of the sub-set of the information obtained. The sub-set of information is obtained by using NS simulator.

In [16], Tumuluru proposed a Multilayer Perceptron (MLP) predictor that does not require a priori knowledge of traffic characteristics of the channel used by the primary users. The problem of Channel state prediction is considered as binary series prediction problem. Binary series is used to obtain input and output that is generated for each channel by sensing the channel status for duration T in every slot. MLP is trained to predict the channel state in next slot using binary series on the basis of the slot status history. Batch back propagation algorithm is used to update the parameters of MLP.

In [17], to predict the channel state based on its history two type of Neural networks are proposed; Time delay neural network (TDNN) and Recurrent Neural network (RNN). Secondary users are assumed to logically divide the PU channel into separate time slots. PU traffic on any channel is assumed to follow Poisson process. TDNN is a Feed-Forward network with a delay line as the network input. RNN is back propagation network with feedback connection from output to its input. The sigmoid function is used for the neurons in hidden layer and output layer. BP algorithm is used for learning and Mean Squared error (MSE) is calculated as a performance measurement.

d) Prediction based on Autoregressive model

Autoregressive model also known as ARM is a model used for linear prediction for time-varying processes. These are commonly used to approximate discrete-time random processes. ARM specifies that the output linearly depends on a stochastic term and its own previous value. An autoregressive model of order p is defined as $AR(p)$. Prediction is made according this rule

$$\hat{X}_T = \sum_{i=1}^{p} \varphi_i \; X_{T-i} + \omega_T$$

Where $\hat{X}_T$ is the predicted state, φ_i is the parameter of the model, X_{T-i} is observation at time $T-i$ and ω_T is the white noise at time T.

In ARM, secondary user first estimates the model parameters $\varphi_{i}, i = 1,2 \ldots\ldots p$, using Yule-Alker equations, maximum likelihood estimation, or other approaches. Then, the history observations are given as input to the prediction rule and the future state of the system is predicted as $\hat{X}_T$.

In [11], a channel prediction model for a fading channel is presented that adopts a second-order ARM process and a Kalman filter. By taking into consideration channel idle probability and temperature, a Bayes risk criterion is presented for spectrum hole detection. Channel variation model is based on second-order autoregressive (AR2) process. Yule- Alker algorithm is used to compute the parameters. Then the state of channel is predicted using Kalman filter. Bayes risk criterion is also studied in this paper. A centralized ALOHA system is considered for randomly distributed primary users and secondary users. Primary user's message arrival process is considered to follow Poisson distribution. There is only one PU channel and channel idle intervals are considered to be exponentially distributed and form a typical M/M/1 queue problem.

In [12], a forward backward autoregressive (FBAR) model for simplified spectrum prediction is proposed. The proposed scheme is based on Autoregressive modelling of decimal equivalent value of binary vector that represents the occupancy states of spectrum hole. This limits the probability of error to LSB (least significant bit) while restoring the predicted decimal value to binary vector and accordingly sub channels that corresponds to MSB(most significant bit) will most likely equivalent to the actual spectrum occupancy status. FBAR is presented to reduce the prediction errors. Modelling of time series is done by solving Yule-Walker equations that are obtained by evaluating the auto-covariance function.

e) Prediction based on moving average

Exponential moving average (EMA) based prediction is also called exponentially weighted moving average (EWMA). This applies weighing factors that decreases exponentially. Recent observations are given more significance as the weighing factor for older data points decreases exponentially, but it does not totally discard the older values. Moving average based predictors are generally used to predict a trend in the given sequence of values. In order-k moving average predictor [13], a sequence of values is taken as input and the next value of sequence is predicted which the average of last k values of sequence is. If the set of historical values are $v_1, v_{2\ldots\ldots} v_n$. The next value is estimated as

$$v_{n+1} = \frac{1}{k} \sum_{i=1}^{k} v_{n-i+1}$$

In [14], EMA based energy prediction method is proposed to predict the energy level in frequency band. Secondary user can skip sensing those channels whose predicted energy level is higher than the predefined threshold value that denotes the existence of primary user. A simple and suboptimal energy detector is used. In EMA based algorithm, the degree of weighing decrease is defined as a constant smoothing factor α. The value of smoothing factor lies between 0 and 1. Larger the value of α, larger would be discount of older observations.

f) Prediction based on Static neighbour graph

In [13], a static neighbour graph based predictor has been proposed that predicts the state based on the current status of its neighbours. To predict the primary user's mobility, precollected topology information can be used if the topology of the network does not change rapidly over the time. A directed graph is constructed that represents the transition history of the primary user. Whenever a user moves from a location i to location j, a directed edge (i,j) is constructed if there is no edge between these two points with the weight 1. If the edge already exist weight 1 is added to the current weight. At the end directed graph is obtained with normalized weight as $\forall i, \sum_j w_{ij}$=1, where w_{ij} is the weight of edge (i,j). Predictor finds the current location i of PU and returns a list of all edges originating from i.

CONCLUSION

In this paper we presented the basic functionalities of Cognitive radio network and discussed different prediction techniques and their applications. Various prediction techniques have been studied over the time to predict the spectrum state to reduce the sensing time and improve the efficiency. However there are certain limitations of each technique. HMM provides accurate prediction and can be used widely but it can mostly be applied on statistical models. Neural network based model on the other hand eliminates the needs for parameter and threshold settings that are required in HMM. Both neural networks and HMM are characterized by high convergence time and complexity. Other techniques also have their benefits as well as drawbacks. Extensive research needs to be done to provide long-term accurate prediction.

REFERENCES

[1] http://www.fcc.gov/oet/info/database/spectrum

[2] D. Cabric, S. M. Mishra, D. Willkomm, R. W. Brodersen, and A. Wolisz, 2005, "A cognitive radio approach for usage of virtual unlicensed spectrum," in 14th IST Mobile and Wireless Comm. Summit, pp. 1-4.

[3] I. F. Akyildiz, W.-Y. Lee, M.C. Vuran, and M. Shantidev, 2006, "Next generation/dynamic spectrum access/cognitive radio wireless networks": a survey, Computer Networks Journal (Elsevier) 50, pp. 2127–2159.

[4] R. Thomas, D. Friend, L. Dasilva and A. Mackenzie, 2006, "Cognitive networks and learning to achieve end-to-end performance objectives*"*, IEEE Communications Magazine, vol. 44, no 12, pp. 51-57

[5] I. F. Akyildiz, Won-Yeol Lee, Kaushik, and R. Chowdhury, 2009, "CRAHNs: Cognitive radio ad hoc networks".

[6] V. U. Kanth, K. R. Chandra, and R. R. Kumar, April 2013, "Spectrum Sharing In Cognitive Radio Networks", International Journal of Engineering Trends and Technology (IJETT) – Vol.4 Issue 4.

[7] X. Xing, T. Jing, Y. Huo, H. Li, and X. Cheng, 2013, "Channel quality prediction based on Bayesian inference in cognitive radio networks", in IEEE INFOCOM.

[8] I. A. Akbar, and W. H. Tranter, 2007, "Dynamic Spectrum Allocation in Cognitive Radio Using Hidden Markov Models: Poisson Distributed Case", South EastCon, IEEE.

[9] Z. Chen, N. Guo, Z. Hu, and R. Qiu, March 2011, "Channel state prediction in cognitive radio, part ii: Single-user prediction", in Proceedings of IEEE South Eastcon, pp. 50 –54.

[10] Z. Chen, Z. Hu, and R. C. Qiu, 2010, "Prediction of channel state for Cognitive Radio Using Higher-Order using hidden Markov model", IEEE.

[11] Z. Wen, T. Luo, W. Xiang, S. Majhi, and Y. Ma, May 2008, "Autoregressive spectrum hole prediction model for cognitive radio systems", in IEEE International Conference on Communications Workshops, pp. 154 – 157.

[12] Ashraf Eltholth, 2015, "Forward Backward Autoregressive Spectrum Prediction Scheme in Cognitive Radio Systems", IEEE.

[13] I. Butun, A. Cagatay Talay, D. Turgay Altilar, M. Khalid, and R. Sankar, April 2010, "Impact of mobility prediction on the performance of cognitive radio networks in Wireless Telecommunications Symposium (WTS) ", pp. 1 –5.

[14] Z. Lin, X. Jiang, L. Huang, and Y. Yao, September 2009, "A energy prediction based spectrum sensing approach for cognitive radio networks" in 5th International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1 –4.

[15] N. Baldo and M. Zorzi, January 2008, "Learning and Adaptation in Cognitive Radios using Neural Networks", 5th IEEE Consumer Communications and Networking Conference (CCNC 2008), pp. 998-1003.

[16] V. K. Tumuluru, P. Wang, and D. Niyato, 2010, "A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio", In IEEE International Conference on Communication (ICC), Cape Town, South Africa, pp. 1-5.

[17] N. Shamsi, A. Mousavinia, and H. Amirpour, November 2013, "A Channel State Prediction for Multi-Secondary users in a Cognitive Radio based on Neural Network", International Conference on Electronics, Computer and Computation (ICECCO)2013, pp. 200-203.