Artificial Neural Networks for Cognitive Radio Network: A Survey

Vishnu Pratap Singh Kirar

***Abstract*—**The main aim of a communication system is to achieve maximum performance. In Cognitive Radio any user or transceiver has ability to sense best suitable channel, while channel is not in use. It means an unlicensed user can share the spectrum of a licensed user without any interference. Though, the spectrum sensing consumes a large amount of energy and it can reduce by applying various artificial intelligent methods for determining proper spectrum holes. It also increases the efficiency of Cognitive Radio Network (CRN). In this survey paper we discuss the use of different learning models and implementation of Artificial Neural Network (ANN) to increase the learning and decision making capacity of CRN without affecting bandwidth, cost and signal rate.

***Keywords*—**Artificial Neural Network, Cognitive Radio, Cognitive Radio Networks, Back Propagation, Spectrum Sensing.

I. Introduction

IN evolution of communication system the necessity of higher data rate is major concern because at present time user not only use voice services but also use video and data services. The electromagnetic radio frequency spectrum has its own limitations and it is tightly regulated and allocated within all countries of the world by International Telecommunication Union (ITU). In any country, local government can provide spectrum license for service providers. Radio spectrum allocation is categorized as licensed and unlicensed band. In Licensed band frequency can used or transmit only in allocated band that they purchased, while unlicensed band can use any frequency. Thus to use optimum frequency, communication system can use different techniques like modulation, attenuation, coding. Many research shows that in fixed spectrum allocation some frequencies are used heavily while some frequencies are not used or partially used. Unused frequency is also known as spectrum hole. The spectrum holes are belongs to licensed user but for some instants these holes are not used by user. The cognitive radio is a device that senses these spectrum holes and make available for unlicensed user. In CR licensed user also known as primary user and unlicensed user as secondary user. The major characteristics of CR is to ability to sense, learn, measure, be aware about communication channel and its availability i.e. spectrum availability and power.

The concept of Cognitive Radio (CR) is first introduced by Mitola in his PhD work [1]. He proposed an idea to enhance effectiveness of wireless communication by make aware to its radio units to utilize its surrounding sources i.e. communication channel. Haykin [2] introduce signal processing and communications realization of CR technology. Cabric, Mishra and Brodersen and also proposed some fundamental issues about CR [3]. All these early contributions introduce spectrum sensing to detect vacant spectrum band and utilize these it.

Artificial Intelligent play an important role in wireless communication specially to sense the surrounding environment. It has ability to learn things and adapt itself according to input and provide output. Cognitive Radio Networks fulfill these requirements. Thus, if we apply ANN on CRN then we achieve maximum performance and maximum utilization of wireless communication.

Human brain learns new things every day, by this behavior he gain knowledge and become more and more intelligent and smarter. ANN adopted the property of human brain and provides solution for non-liner and probabilistic problems. Similarly, if we want CR to work more intelligently then we should enable CR to learn. Various learning techniques of ANN enable CR to learn. Meanwhile all intelligent algorithms are not useful for CR. Some learning algorithms can be used to predict communication performance but genetic algorithms are suitable for transceiver's parameters. Thus, combination of different kind of intelligent algorithms is better for CR. Some of them are ANN, ANFIS, reinforcement learning genetic algorithms, and hidden Markov models reinforcement algorithms. In this survey paper we discuss various learning techniques of ANN that implemented on CRN.

This survey paper is organized as follows: sections II describes and compare different learning models for cognitive radio network. Section III explains ANN and its learning algorithms. We mainly discuss the Back propagation (BP) algorithm and Feed Forward Neural Network (FFNN). Section IV discusses the various ANN that implemented on CRN and provide a comparison between them. Finally we conclude the paper in Section V.

II. Deferent Learning Models for Cognitive Radio Networks

Cognitive radio has special ability of learning about its surrounding communication system and remembers the information like knowledge. According to situation if CR needs help from previous knowledge then it can retrieve information. It is also useful to make an accurate decision.

In CRN for spectrum sensing, spectrum behavior, spectrum selection, performance and other different parameters, different learning models are implemented. Some of them are

Vishnu Pratap Singh Kirar is with the Computer Science Department, University of Bedfordshire, Luton, United Kingdom. (Phone: +44 7405400182; +91 9826020913; e-mail: Vishnu.kirar@study.beds.ac.uk, vishnupskirar@live.com).

Machine Learning, Collaborative filtering and self-learning model. Neural Network, Genetic Algorithm, Markov Model and Game Theory are used for dynamic parameters like spectrum and channel selection. Neural Network is best suitable solution for pattern recognition and probabilistic problems. Thus, ANN is applying for transmission rate, signal prediction, decision making in CRN [4]. Self-organizing learning techniques are implemented for detection of surrounding spectrums. Different learning techniques are explained in Table I.

TABLE I
LEARNING MODELS FOR COGNITIVE RADIO NETWORK

Learning Model	Techniques used for	Advantages	Limitations	Observation and scope
Markov Model	Dynamic Spectrum Access	Improved throughput	Provides some undesirable solutions	Also implemented in cognitive engine
Q-Learning	Modelling, Cognitive cycle	Higher performance rate	Only for local parameters	Realization of Cognitive engine
Game Theory	Channel Selection	Higher utilization rate	Performance depends upon particular parameter selection	Ability to enhance the capacity for next generation services
Fuzzy Logic	Transmission rate prediction	Less complexity	Need some global information in addition	Can Predict other parameters of CRN
Genetic Algorithms	Optimization	Excellent for parameter optimization	Performance depends upon particular parameter selection	Can be update input weight automatically
Neural Networks	Dynamic channel Selection, Cognitive Engine,	Learn in absence of previous information	Performance depends upon particular parameter selection	Can also implemented in all aspects of CRN

III. ARTIFICIAL NEURAL NETWORK

ANN is identical to the biological cells of the human brain, it consist of a number of interconnected processors also known as neurons. Its neuron model, architecture and learning algorithms can explain ANN. Architecture refers to a number of neurons and the links connected to these neurons in different layers. The link between neurons is known as weight and it is adjusted during the training phase. Neuron model processes the information that they receive as input and provide an output. Thus, there is a fixed output for a particular input information, attribute or data. Learning algorithms are essential and fundamental characteristic of ANN and used for its training. During the training weights are automatically updated using the negative gradient of Mean Square Error (MSE). If network find an error than this error signal is again feed into the lower layer of ANN.

ANN consists of number of neurons and they are interconnected by weighted links. Generally ANN structure made by three layers: incoming neurons layer which receive the incoming signals, hidden neuron layer and output neuron layer. The incoming signals (x_i) are multiplied by the corresponding weights (w_i) of the links and a bias term (b_i) is added. All these terms now multiplied to form an input to next layers neuron, which is subjected to a nonlinear function i.e. activation function like sigmoidal or hyperbolic. A single neuron classifier model is shown in the Fig. 1 [5].

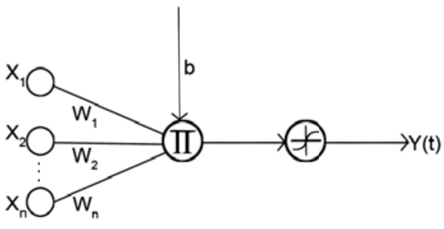

Fig. 1 Single Neuron as a classifier

Finally, the standard output *y(t)* define as:

$$y = \prod_{i=1}^{n} (w_i x_i + b_i) \tag{1}$$

A. Feed forward Neural Network (FFNN)

Feed Forward (FF) neural network have most powerful mapping techniques. Applying on multiplicative network it gives faster learning time and excellent approximation capacities. Its results are better than multi-layer perceptions because it can process higher order information. Multiplicative Neuron Model (MNM) is implemented in higher order neural networks.

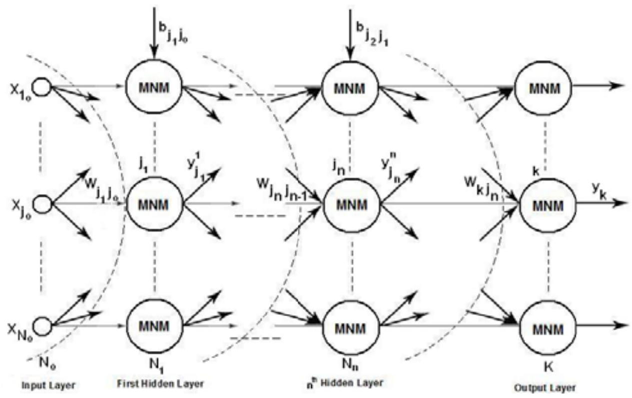

Fig. 2 Pi Neuron Based MNM

A Pi neuron based ANN is shown here in Fig. 2. In this MNM, at each neuron adds all weights incoming to it along with bias, now these summations are multiplied and generate an output for this neuron. Now this output will become an input for next layers neuron. A bipolar activation function is applied before the final output. These MNM neurons look very complex at the first but it required a less number of parameters as compare to other neuron models [6].

$$w_i^{new} = w_i^{old} + \Delta w_i \tag{2}$$

$$b_i^{new} = b_i^{old} + \Delta b_i \tag{3}$$

B. Back Propagation (BP) Algorithm

The Back Propagation (BP) algorithm was first introduced by Rumelhart, Hinton and Williams in 1986 [7]. BP provides effective learning for many practical applications. In BP weight change is calculated by using two term algorithms, leaning rate and momentum factor. BP algorithm faces problem of local minima and slow conversion speed. Zweiri [8] propose proportional factor of two-term BP to reduce complexity and computational cost of ANN. The BP method calculates the first derivative for estimating the gradient. Thus, it is the most popular among other methods. On BP various approaches are proposed to avoid local minima and they are based on selection of momentum and dynamic variation of machine learning along with suitable cost function and activation function. Momentum coefficient and learning rate selected according to the previous weight update of neuron and coefficient of downhill gradient [9]. For fast minimum search Drago et al. [10] proposed an adaptive momentum BP. Chen et al. proposed sequence of weighting vector at the learning phase. Vishnu et al. [11] implemented three terms BP on XOR problem to solve the local minima problem.

The BP learning algorithm with multiplicative neural model explained in Fig. 3.

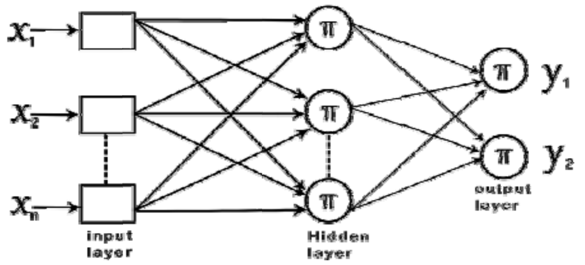

Fig. 3 Multiplicative Neural Network Model

The standard algorithm can modify by applying momentum term and proportional factor term. The momentum term obtain by quantization of weight change. Variations in slop of error suppress the oscillation and gradient due to anomalies. It prevents ANN to fall in to local minima problem. Saturation behavior of activation function keeps the convergence speed relatively slow or almost constant. The problem of convergence speed is resolved by adding proportional factor between the training targets and outputs. The improved term BP weight and bias can be calculated as

$$\Delta w_i^{improved} = \Delta w_i + \beta \Delta w_i^{old} + \gamma(y-d) \tag{4}$$

$$\Delta b_i^{improved} = \Delta b_i + \beta \Delta b_i^{old} + \gamma(y-d) \tag{5}$$

β is the proportional term. The error function optimization depends on these independent quantities [11].

IV. Various ANN Implemented on CRN

CRN is a new emerging technology that attracts researchers. Many of them apply various ANN methods on it and achieve excellent results because the some characteristics and properties of ANN and CNR are similar especially the intelligence toward the sensing or tracking. In this section we discuss some proposals that presented by researchers. Performance of ANN in CRN is shown in Table II.

A. Proposal 1

Baldo and Zorzi [12] proposed a Multilayered Feed forward Neural Network (MNFF) for performance of real-time communication for Cognitive Radio System. They use the function approximation of MFNN to obtain environment measurement and performance measurement. Now by using the sub set of this information MFNN is train with Back Propagation (BP) algorithm. The CR is now train and able to perform in various different environments. NS-Miracle simulator used to obtain the sub set of information. This performance is compared with Bianchi’s model [13]. Bianchi proposed kalman filter for performance calculation. After comparing the results Baldo and Zorzim [12] found that Bianchi’s model have much more complexity and have less accuracy of throughput performance. MFNN provides good accuracy and it is very flexible. It increases the performance and optimizing the configuration of CRN.

B. Proposal 2

Zhang and Xie [14] design a neural network for decision making of CR engine, which is based on evaluation, and learning. CR engine is based on Genetic Algorithm (GA). GA works on various parameters of system chromosomes. These chromosomes are based on knowledge and help to make a decision. For this both changeable information (signal rate, automatic repeat request (ARQ), FCC, bandwidth, modulation and encryption) and unchangeable information (licensed user or owner and cost) are collected and processed. These information become input for neural network and it gives best decision as the output. In this study Levenberg-Marquardt (LM) algorithm is used for training and performance index is Mean Square Error (MSE). This neural network has great ability of non-linear reflection, it need very less previous knowledge i.e. information and it also has a less complex structure. It can easily simulate the information at input and the output for complex network. Zhang and Xie [14] compare their model with Rieser’s cognitive radio engine. Rieser’s model has limitations because its decision is based only on unchangeable information [15]. On the other hand, neural network model proposed by Zhang and Xie [14] is able to make decision for CR engine, which is based on both changeable and unchangeable information.

C. Proposal 3

Zhu et al. [16] propose an Adaptive Resonance Theory (ART-2) Neural Network for channel sensing. It also satisfies the cognitive Wireless Mesh Network (WMN) structure, which also combines with signal broadcast system. Zhu *et al.* also consider that WMN coexist with Wireless Regional Area Network (WRAN). WRAN distributes the signal spectrum into separate sub-bands. These sub-bands perform the channel sensing. WMN consist of clusters and multi channels, so Mesh

Point sense the information and inform to cluster head. The data fusion in channel sensing is similar to pattern recognition problem thus ART-2 is more suitable for CRN. ART-2 has ability to self-organize the input and creates resonance state and associate with categories. These categories follow specific prototype patterns. Neural network accept all these patterns of same category as an input and train the system. After the training we select the most significant node. If network not provide any node then it is assumed that MP provide wrong information. Zhu et al. [16] compare their simulation results with Bayesian Draft Protocol and found that their network provides better accuracy.

D. Proposal 4

Tumuluru et al. [17] proposed a spectrum predictor for cognitive radio using Multilayer Perceptron (MLP) Neural Network. This MLP has special characteristic that it does not require previous knowledge or data of traffic characteristics of licensed user. Neural network creates mapping function between input data and output data. This data is in the form of binary which is obtained by channel sensing during different time. When licensed user is active then channel status is busy and when user is absent then channel is idle. In ANN we represent this situation as a two-class problem. Binary representation for busy and idle condition is 1 and -1 respectively. MLP predictor uses the BP algorithm. For training channel sensing data is provided as input. Neural network maps input data with output data. In this problem output data is 1/-1. We have desired output and neural network provides desired output. Difference between desired and estimated output provides error. The less error provides the better results and accuracy i.e. prediction. Tumuluru et al. compare their results with HMM based spectrum prediction scheme [18], [19], which does not provide details about length of observation sequence and number of states. Spectrum prediction CRN save the sensing energy and improve spectrum utilization of communication channel.

E. Proposal 5

Cai et al. [20] proposed an Incremental Self-Organizing Map integrated with neural Network (ISOM-HNN) for signal classification in CRN. This approach detects unknown radio signals in wide communication network or channel. ISOM improves real time learning performance and HNN improves learning along with prediction accuracy. ISOM provide incremental learning to SOM. ISOM update the weight of neurons by calculating the total number of inputs in neurons. As number of input is increased the magnitude of weight is also increases. By this method ISOM grows dynamically and detect the unknown signals continuously. For learning, prediction and association of HNN, the modified Hebbian learning algorithm is proposed. ISOM-HNN discards the dependency of data dimensionality and it enhances capacity of CRN to identify authorized and unauthorized radio signal in communication spectrum.

F. Proposal 6

Tang et al. [21] propose an Artificial Neural Network for spectrum sensing of CRN under low Signal-to-Noise Ratio (SNR). Primary user has Amplitude Modulation (AM) signals. Secondary user perform ANN based detection method to sense whether the primary user occupy the channel or not. The attributes of four input neurons are energy and three cyclostationary values. At the training phase, weights and threshold of each neuron are updated at each-iteration. Training followed the feature abstraction. Additive White Gaussian Noise (AWGN) is added to AM signals to introduce SNR in network. Proposed ANN has advantages of cyclostationary values detection and energy detection. This ANN has less computational complexity and reduces the interference in CRN.

TABLE II
PERFORMANCE OF ARTIFICIAL NETWORK IN COGNITIVE RADIO NETWORK

Authors	Uses for CRN	Input Attributes	Output Attributes	Activation Function	Layers	Considerations
Baldo and Zorzi [12]	Performance characterisation of component	Received Frames Idle Time SNR	Throughput ReliabilityDelay	Sigmoid function	Multilayer forward NN	Number of users in CRN
Zhang and Xie [14]	Decision Making	ARQ, FCC, Signal Rate, Bandwidth, Modulation, Encryption, Cost, Owner	Mean Square Error (MSE)	Sigmoid Function	Multilayer (ML) BP NN	System Chromosomes
Zhu et al. [16]	Channel Sensing	Prototype Patterns	Mean Square Node	Poison Distribution	ART-2 NN	Data Fusion
Tumuluru et al. [17]	Spectrum Prediction	Traffic Characteristics	Two classes (1/-1) MSE	Sigmoid function	MLBP NN	Prior Knowledge
Cai et al. [20]	Signal Classification	Channel bandwidth, Dwelling time	Mohalanobis distance	Incremental Function	ISOM-HNN	Data dimensionality
Tang et al. [21]	Spectrum Sensing	Energy Cyclostationary values	Cyclic Spectrum	Threshold function	BPNN	SNR AWGN
Shamsi et al. [22]	Predictive Modelling Multi secondary user	Traffic Distribution	MSE	Hyperbolic function	Feedforword NN BPNN	Delay Line
Tan et al. [23]	Frequency Allocation	Frequency	MSE	Sigmoid Function	BPNN	Weight at different time
Zhang et al. [24]	Cooperative spectrum sensing	Probability forecast of Fusion Centre	MSE	Threshold function	BPNN	AWGN SNR
Gatla et al. [25]	Performance (Throughput, Data Rate)	Link quality Signal Strength	MSE	Sigmoid Function	Focused time delay Neural Network	FTDNN

G. Proposal 7

Shamsi et al. [22] design Time Delay Neural Network (TDNN) and Recurrent Neural Network (RNN) for predictive modeling and multi secondary user scenario in CRN. It improves the spectrum utilization. It helps the secondary user to choose best possible and available communication channel. The error for prediction is almost zero in these methods. Secondary user divide licensed channel in to small time slots. For each time slot secondary user sense the spectrum holes. In ideal condition secondary user sense the vacant channel correctly. TDNN is a Feed Forward network and a delay line is applied to its input. RNN is back propagation network and it has feedback connection from output node to input node. This feedback generates a pattern for each time instance. Primary user traffic distribution as a binary sequence work as an Input for training of TDNN and RNN. Two data sets are generated by these networks by using feedback pattern and binary sequence. For learning of TDNN and RNN, BP algorithm is used. After successful training, MSE is calculated as performance of CRN. Secondary user uses the channel status predictor with maximum priority. Shamsi et al. [22] also explain the spectrum resource security. These networks help to secondary user to sense the spectrum holes and make them to accessible. It also provides accurate activity of primary user. Thus it also reduces the interference. TDNN and RNN both have highest prediction probability.

H. Proposal 8

Tan et al. [23] propose an ANN to solve a frequency allocation problem in CR. In CR primary user has license or right to use frequency any time. On the other hand, secondary user only use at particular time. User has different weight in CR. Thus, two hypotheses are adopted. Firstly, multi user with different weight at same time and secondly, single user with different time. BPNN train the weight of each user for same time instant and different time. The output provides decrease distance between actual output and expected output. In CRN, demand of frequency is changes over the time. Thus, user has to keep in touch with the environment. The network designed by Tan *et al.* provides a faster and accuracy toward frequency allocation due to less complexity in computation.

I. Proposal 9

Zhang et al. [24] proposed an ANN for cooperative spectrum sensing of CRN. Fusion centre is used to find the probability of weights. Secondary User/Unit (SU) sense for primary user/unit (PU) and send the information to fusion centre. Fusion centre is used to find the probability of weights. And it is work as an input of ANN. Spectrum sensing is divided into three hypotheses in this model. These are spectrum sensing of individual SU, communication between SU and fusion centre, and fusion scheme. For training phase SU provide the sensing information as input and after the training SU stop to work. Now fusion centre also stop to send reference signal to PU. Thus PU gets knowledge about probability of SU weight. As SU and PU are both involve in spectrum sensing of CRN thus it is known as cooperative spectrum sensing. This model provides the excellent performance of probability and detection probability.

J. Proposal 10

Gatla et al. [25] proposed a learning model using neural network to calculate performance of CRN and its parameters like throughput and data rate. This network uses the non-linear transfer function to map linear as well as non-linear input and output. The linear output has two classes and generally represented by 1 and -1. Preprocessing is applied to normalize the data. Focused Time-Delay Neural Network (FTDNN) provides delay lines in the input. To update the weight and the bias, LM algorithm is used. To measure the data rate, bit rate and signal strength works as an input of NN. This model explains the relation between signal strength and data rate of CRN.

V. CONCLUSION

In present scenario, wireless network spectrum resources are backbone of communication across the world and it has potential to rapid increase. There are a lot of possibilities in the research field of CRN especially in aeronautical and satellite communication systems. In this survey paper we discuss various implementation presented by different authors. From the given proposals we conclude that BP algorithm is best suitable algorithm for ANN. Sigmoid function provides best result in ANN. And most popular method to describe output parameter for ANN is Mean Square Error (MSE). The performance of proposal presented by Shamsi et al. [22], give the most significant and accurate results. The accuracy of the network is higher than other proposal that describe above. The MSE for network is almost zero. In general the proposal of Shamsi et al. [22] is best among the other proposals.

The main importance of CRN is to sense the spectrum or prediction. If CRN has effective sensing power than then it can use all the resources of communication channel. ANN has very good ability for recognition and prediction of physical and logical attributes. These abilities of ANN are implemented on CRN to achieve maximum performance of CRN. It also increases the accuracy and effectiveness of CRN.

REFERENCES

[1] J. Mitola, “Cognitive Radio: An Integrated Agent Architecture for Software define Radio,” Ph.D. dissertation, Royal Institute of Technology (KTH), Sweden, 2000.

[2] S. Haykin, "Cognitive Radio: Brain-Empowered Wireless Communications," IEEE Journal on Selected Areas in Communications, vol. 23, no. 2, pp. 201-220, February 2005.

[3] D. Cabric and R. W. Brodersen, "Physical Layer Design Issues Unique to Cognitive Radio Systems," in Proc. of PIMRC-2005, pp. 759-763, September 2005.

[4] M. Venkatesan, A. V. Kulkarni, “Soft Computing based Learning for Cognitive Radio,” international journal on Recent Trends in Engineering and Technology, vol. 10, issue 1, pp. 112-119, January 2014.

[5] K. Burse, A. Mishra, A. Somkuwar, “Convergence Analysis of Complex Valued Multiplicative Neural Network for various Activation Functions,” IEEE International Conference on Computational Intelligence and Communication System (CICN 2011), pp. 279-282, October 2011.

[6] V. P. S. Kirar, K. Burse, R. N. Yadav, S. C. Srivastav, “A Compact Pi Network for Reducing Bit Error Rate in Dispersive FIR Channel Noise

Model," Proceedings of World Academy of Science, Engineering and Technology," vol. 38, pp. 235-238, Ferbuary 2009.

[7] D.E. Rumelhart, G.E. Hinton and R.J. Williams, "Learning representations by back -propagating errors," Nature (London), 323, 533-536, 1986.

[8] Yahya H. Zweiri, Lakmal D. Seneviratne, and Kaspar Althoefer. 2005. Stability analysis of a three-term backpropagation algorithm. *Neural Netw.* 18, 10 (December 2005), 1341-1347.

[9] Y. F. Yam and T.W.S. Chow, "Extended Back Propagation Algorithm," Electronics Letters, vol. 29(19), pp. 1701-1702, 1993.

[10] G. P. Drago, M. Morando and S. Ridella, "An Adaptive Momentum Back Propagation, Neural Computing and Application," vol. 3, pp. 213-221, 1995.

[11] V. P. S. Kirar, K. Burse, M. Manoria, "Improved Back Propagation Algorithm for Complex Multiplicative Neuron Model," Proceedings of Springer conference, Information Technology and Mobile Communication, Communication in Computer and Information Science (CCIS), vol. 147, pp. 67-73, April 2011.

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

[13] G. Bianchi, "Performance Analysis of the IEEE 802.11 Distributed Coordination Function," IEEE Journal on Selected Areas in Communications, vol. 18, no. 3, pp. 535-547, March 2000.

[14] Z. Zhang and X. Xie, "Intelligent Cognitive Radio: Research on Learning and Evaluation of CR Based on Neural Network," Proceedings ITI 5th International Conference on Information and Communications Technology (ICICT 2007), pp. 33-37, December 2007.

[15] C. J. Rieser, T. W. Rondeau, C. W. Bostian, and T. M. Gallagher. "Cognitive RadioTest bed: Further Details and Testing of a Distributed Genetic Algorithm Based Cognitive Engine for Programmable Radios," IEEE MILCOM, October 2004.

[16] X. Zhu, Y. Liu, W. Weng, and D. Yuan, "Channel Sensing Algorithm based on Neural Network for Cognitive Wireless Mesh Network," in Proceedings of IEEE International Conference on Wireless Communications (WiCom), pp. 1-4, 2008.

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

[18] A. Akbar and W. H. Tranter, "Dynamic Spectrum Allocation in Cognitive Radio using Hidden Markov Models: Poisson Distributed Case," in Proceedings of IEEE SoutheastCon, pp. 196-201, March 2007.

[19] C. H. Park, S. W. Kim, S. M. Lim and M. S. Song, "HMM based Channel Status Predictor for Cognitive Radio," in Proceedings of Asia-Pacific Microwave Conference (APMC), pp. 1-4, December 2007.

[20] Q. Cai, S. Chen, X. Li, N. Hu, H. He, Y.-D. Yao, and J. Mitola, "An Integrated Incremental Self-Organizing Map and Hierarchical Neural Network Approach for Cognitive Radio Learning," The 2010 International Joint Conference on in Neural Networks (IJCNN), pp. 1-6, July 2010.

[21] Yu-Jie Tang, Qin-Yu Zhang, Wei Lin, "Artificial Neural Network based Spectrum Sensing Method for Cognitive Radio," IEEE conference on wireless communications and mobile computing, pp. 1-4, September 2010.

[22] N. Shamsi, A. Mousavinia, H. Amirpour, "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, November 2013.

[23] X. Tan, H. Huang, L. Ma, "Frequency Allocation with Artificial Neural Networks in Cognitive Radio System," IEEE TENCON Spring Conference 2013, pp. 366-370, April 2013.

[24] T. Zhang, M. Wu. C. Liu, "Cooperative Spectrum Sensing based on Artificial Neural Network for Cognitive Radio System," 8th International Conference on Wireless Communication, Networking and Mobile Computing (WiCOM) 2012, pp. 1-5, September 2012.

[25] V. Gatla, M. Venkatesan, A. V. Kulkarni, "Feed Forward Neural Network based learning scheme for cognitive radio systems," Third International Conference on Computational Intelligance and Information technology, CIIT 2013, pp. 25-31, October 2013.