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Technique for Predicting Data Rate for Cognitive Radio Using Neural Network

Rita Mahajan[1], Dr. Deepak Bagai[2]
[1]Assistant Professor, [2]Associate Professor E&EC Dept., PEC University of Technology, Chandigarh, India

Abstract
Significant problems confronting wireless communications, are scarcity and deployment difficulty. The deployment problem is a process problem i.e., frequency allocation is fixed and is done so by complex collaboration and coordination between countries and systems, respectively. The limited available spectrum and the inefficiency in the spectrum usage necessitate a new communication paradigm to exploit the existing wireless spectrum opportunistically called cognitive radio technology. In this paper we have proposed a learning technique using neural network to be used in cognitive radio so that it can predict the data rate. Performance of learning scheme has been observed using Matlab simulations and found that Focused Time Delay Neural Networks are good candidate for cognitive radios.

Keywords — cognitive radio, neural network, dynamic spectrum access, wireless communication.

I. INTRODUCTION

The requirement for higher data rates is increasing as a result of the transition from voice-only communications to multimedia type applications. Given the limitations of the natural frequency spectrum, it becomes obvious that the current static frequency allocation schemes cannot accommodate the requirements of an increasing number of higher data rate devices. As a result, innovative techniques that can offer new ways of exploiting the available spectrum are needed. Cognitive radio arises to be a tempting solution to the spectral congestion problem[1].

Fortunately, recent research efforts to characterize actual spectrum usage in both urban and rural areas have shown that more spectrum is available than conventionally realized[2]. Defense Advanced Research Projects Agency (DARPA) asserts that the upper bound of usage is only 6% as shown in the sanitized power spectrum distribution (PSD) of Fig. 1. We would find that:

1) Some frequency bands in the spectrum are largely unoccupied most of the time.
2) Some other frequency bands are only partially occupied.
3) The remaining frequency bands are heavily used.

The underutilization of electromagnetic spectrum leads us to think in terms of spectrum holes, for which we offer the following definition:

"A spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user".

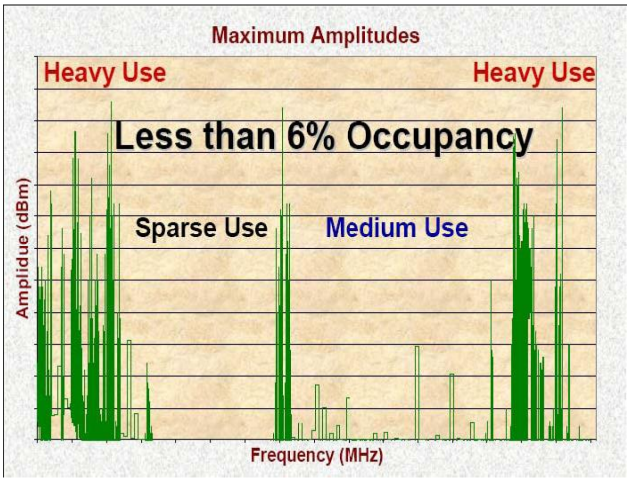

Fig. 1. View of the actual availability of spectrum.

The inefficiency in the spectrum usage necessitates a new communication paradigm to exploit the existing wireless spectrum opportunistically. Dynamic spectrum access is proposed to solve these current spectrum inefficiency problems. DARPA's approach on Dynamic Spectrum Access networks, aims to implement the policy based intelligent radios known as cognitive radios[2].

II. COGNITIVE RADIO

The term cognitive radio identifies the point at which wireless personal digital assistants (PDAs) and the related networks are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to detect user communications needs as a function of use context and to provide radio resources and wireless services most appropriate to those needs.

A cognitive radio adds both a sensing and an adaptation element to the wireless network [3]. Four new capabilities embodied in cognitive radios will help enable dynamic use of the spectrum: flexibility, agility, RF sensing, and networking [2-3].

- Flexibility is the ability to change the waveform and the configuration of a device.
- Agility is the ability to change the spectral band in which a device will operate.
- Sensing is the ability to observe the state of the system, which includes the radio and, more importantly, the environment. It is the next logical component in enabling dynamics.
- Networking is the ability to communicate between multiple nodes and thus facilitate combining the sensing and control capacity of those nodes.

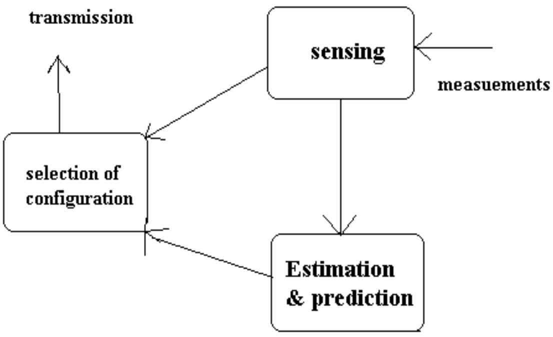

Fig. 2: Representation of cognitive radio cycle

In this respect, future cognitive radio devices will have the capability, to choose on the fly the radio configuration, by taking into account the context of operation (device status and environment aspects), goals, policies, profiles and capabilities, and machine learning (for representing and managing knowledge and experience). Simplified cognitive radio cycle is shown in Fig. 2. During sensing various environmental conditions are probed and these are used to estimate and predict the performance of various configurations[7]. In the final phase the best configuration is selected.

III. RELATED WORK

The problem of spectrum occupancy status from the perspective of binary time series for CR is considered in paper[4]. Time series models derived are tested in terms of raw residuals. Two types of spectrum occupancy schemes, namely deterministic and non–deterministic schemes, are considered. The performance of the predictor suffered in case of the non-deterministic nature of the binary series. Hidden Markov Models (HMMs) to model and predict the spectrum occupancy of licensed radio bands is used in paper[5]. The proposed technique can dynamically select different licensed bands for its own use with significantly less interference from and to the licensed users. But the accuracy of the prediction was not provided. Another HMM based predictor was also proposed in [6], but it only deals with deterministic traffic scenarios, but it is not applicable for the actual environment. HMM based spectrum and data rate prediction schemes has some drawbacks such as determining an optimal model is difficult, a large memory space is required to store the past observations and high computational complexity is required for estimation of model[7]. The neural network predictor is trained only once in an offline fashion when the observed process is stationary. Once the neural networks are trained, the computational complexity is significantly reduced[8-9].

IV. REVIEW OF ARTIFICIAL NEURAL NETWORKS

The first artificial neural was presented by the neurophysiologist W. McCulloch and the logician W. Pits in 1943 for the study of the human brain[5]. The idea of artificial neural network (ANN) was then applied to computational models. Modeled on a nerve plexus, an ANN is nothing more than a set of nonlinear functions with adjustable parameters to give a desired output. A neural network consists of a pool of simple processing units, the 'neurons'. Within NNs three types of neurons are distinguished: input neurons which receive data from outside the NN and are organized in the so called input layer, output neurons which send data out of the NN and generally comprise the output layer, and hidden neurons whose input and output signals remain within the NN and form the so called hidden layer (or layers) as shown in Fig. 3.

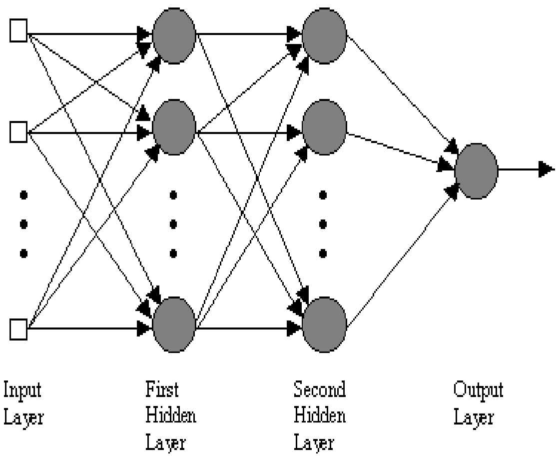

Fig. 3: Artificial Neural Network

The steps for computing the output of a single neuron are as follows:

(1) Compute the weighted sum of inputs to the neuron.

(2) Add the bias to the sum.

(3) Feed the sum as an input to the activation function of the neuron.

The output of the activation function is defined to be the output of the neuron. These steps can be summarized in the following formula: Output = $A(\sum w_k * I_k + \text{bias})$ where A is the activation function of the neuron, w_k is the weight of the k^{th} in-edge, I_k is the input carried across the k^{th} in-edge, and bias is the bias of the neuron. This can be represented by the Fig. 4.

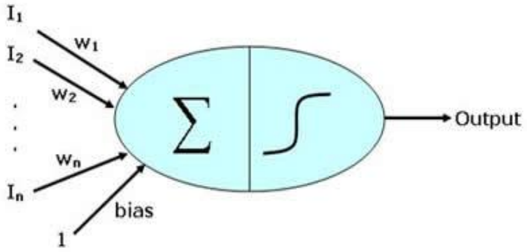

Fig. 4: Single Neuron as Processing Unit

Some type of activation functions can be used for that reason, such as a linear function, or a smoothly limiting function often being a sigmoid (S-shaped) function like the logistic- sigmoid transfer function, or hyperbolic tangent sigmoid transfer function or step function based on the algorithm to be used as shown in Fig 5.

Activation Functions	
Name	**Formula**
Identity	$A(x) = x$
Sigmoid	$A(x) = \frac{1}{1+e^{-x}}$
Tanh	$A(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$
Step	$A(x) = \begin{matrix} -1 & if\ x < 0 \\ 1 & if\ x \geq 0 \end{matrix}$

Fig. 5: Activation Functions

The advantage of neural networks over statistical models is that it does not require a priori knowledge of the underlying distributions of the observed process. Therefore, the neural networks offer an attractive choice for modeling the predictor.

It is apparent that the NN derives its computing power through, first, its massive parallel distributed structure and, second, its ability to learn and therefore to generalize. The remarkable works on the study of neural networks can be contributed to several researchers. Rumelhart proposed the Error Back-Propagation Neural Network (BPNN, 1986) which is effective to solve many application problems. Hopfield proposed the Hopfield Neural Network based on the research of Ising model in 1984. Hardy, Harder and Desmarais proposed the Radial Basis Function Neural Network (RBFNN).

V. SIMULATION AND RESULTS

The focus is on to predict the achievable transmission data rate from a set of reference values that uniquely characterize each of the operating standard modes, e.g. according to IEEE 802.11g specifications, the achievable raw data rates are in the set R1={6, 12, 24, 36, 48, 54} in Mbps. It has been assumed that the proposed neural network has been tunned to WLAN using IEEE 802.11g. The probabilistic data has been generated using lowest probability to the highest data rate and highest probability to the lowest data rate. This is due to the fact that probability of occurrence of spectrum hole at lower data rate is more. The probability distribution used for data rates {6, 12, 24, 36, 48, 54} in Mbps is {.5 .2 .1 .1 .06 .04} respectively. The simulations have been done in Matlab. The size of randomly generated time series data set is 2000 for training.

The neural network that has been selected is Focused Time-Delay Neural Network (FTDNN) which is a feed-forward input-delay back-propagation network, and consists of a feedforward network with a tapped delay line in the input and is shown in Fig. 6. The duration of each slot in the tapped delay line is set equal to the predefined time intervals used for monitoring reasons, and with default value set equal to one timestep. Parameters used for simulations are given in Table 1.

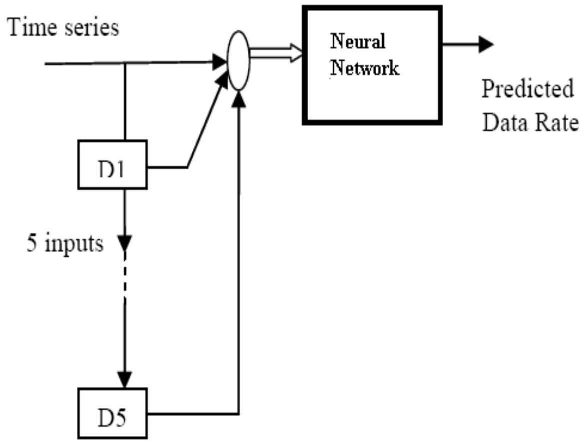

Fig. 6: Focused Time Delay Neural Network

TABLE 1: PARAMETERS FOR NEURAL NETWORK

Net Type	FTDNN
Training data set size	2000
No. of hidden neurons	20
Delay elements	5
Training function	Trainlm
Epochs	100
Learning rate	.001

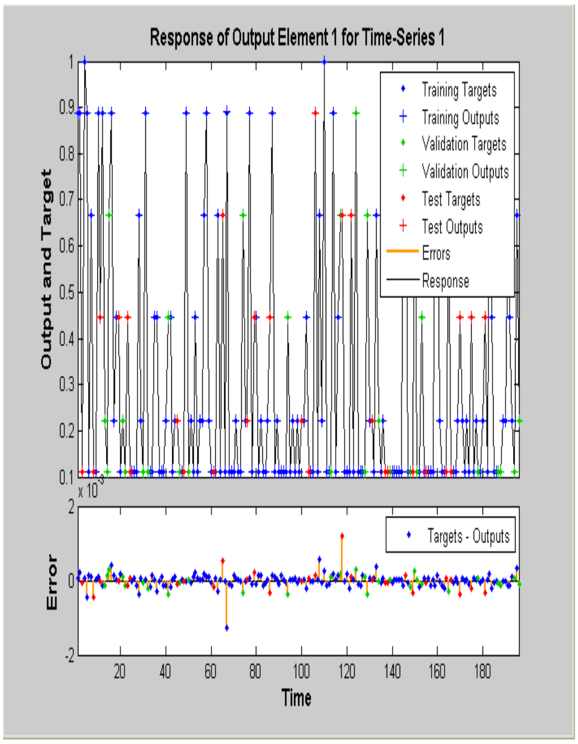

Fig. 7: Response of output element of FTDNN

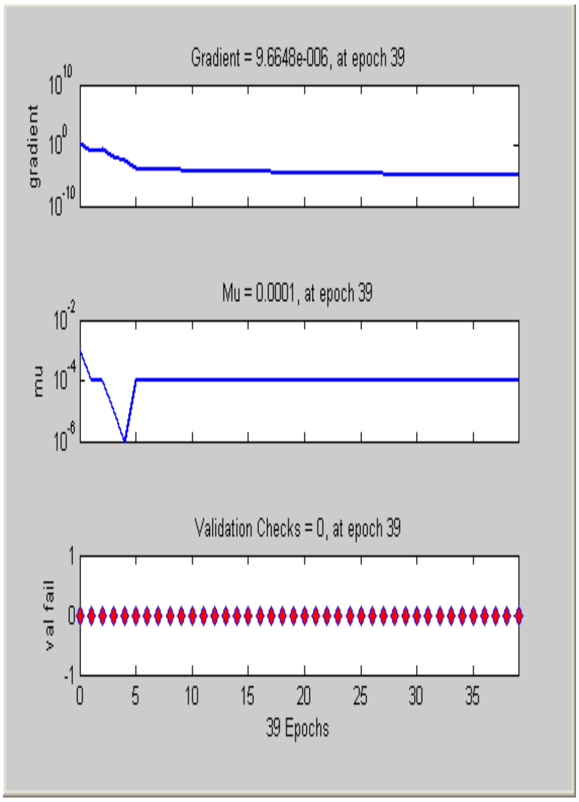

Fig. 8: Gradient and Validation Check

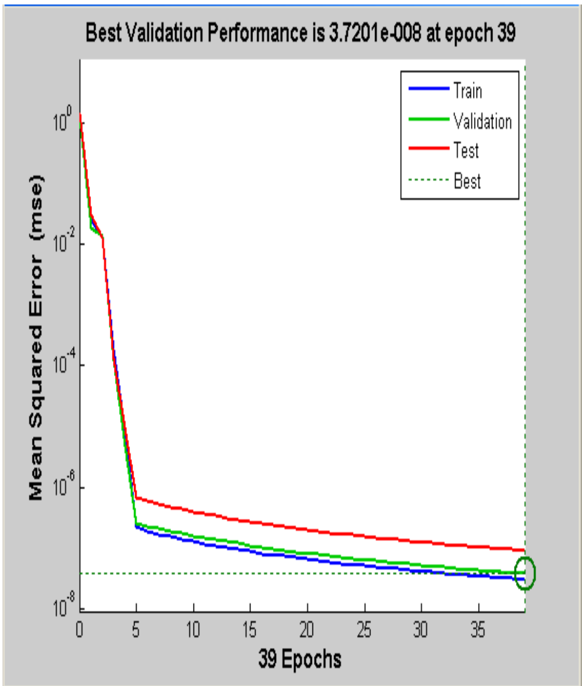

Fig 9: Performance of network in terms of MSE

It has been observed from Fig. 7 that during that when data set for testing is applied which is 10% of total data set, the error in prediction is around 5%. Fig.8 shows when validation data set is applied, almost no validation fail for 39 epoches. The performance matrices (Mean Square Error) MSE is less than 10^{-6} in 39^{th} epoch as shown in Fig. 9.

VI. CONCLUSIONS

This paper introduces and evaluates learning schemes that are based on artificial neural networks and can be used for discovering the performance (e.g. data rate) that can be achieved by a specific radio configuration in a cognitive radio system. So predicted data rate can be used to decide the next radio configuration. In order to design and use an appropriate neural network structure, performance analysis has been done in simulation environment. The results have been presented and discussed in order to show the benefits of incorporating neural network based learning schemes into cognitive radio systems.

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