IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331
PP 10-14
www.iosrjournals.org

Spectrum Predictor Model for Cognitive Radio

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ABSTRACT: *The Cognitive Radio (CR) technology enables the unlicensed users to share the spectrum with the licensed users on a non-interfering basis. Spectrum sensing is an important function for the unlicensed users to determine availability of a channel in the licensed user's spectrum. However, spectrum sensing consumes considerable energy which can be reduced by employing predictive methods for discovering spectrum holes. Using a reliable prediction scheme, the unlicensed users will sense only those channels which are predicted to be idle. By achieving a low probability of error in predicting the idle channels, the spectrum utilization can also be improved. In this paper, the spectrum predictor using the neural network model, multilayer perceptron (MLP) is designed, which does not require a prior knowledge of the traffic characteristics of the licensed user systems. In cognitive radio networks, it is difficult to obtain the statistics of channel usage by the primary users a priori. 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 channel status predictor. One of the major goals of cognitive radio (CR) is to alleviate the inefficient use of the spectrum. CR can sense the spectrum steadily and gather information about the evolution of the spectrum in time. Spectrum occupancy information can be used for both learning the usage of the spectrum and predicting the future occupancy status. In this paper, the use of binary time series for spectrum occupancy characterization and prediction is proposed.*
Keywords - *Cognitive Radio, Spectrum Prediction, Soft Computing techniques, feed forward networks*

I. INTRODUCTION

A spectrum survey conducted by the (FCC) U.S. Federal Communications Commission [1] showed that the present static spectrum allocation policies have caused spectrum scarcity among the unlicensed user systems and under utilization of spectrum among the licensed user systems (e.g., UHF band). Opportunistic spectrum access (OSA) techniques can be adopted by the unlicensed user systems to meet the spectrum requirements of their users. Recently, the FCC has approved opportunistic spectrum access by the unlicensed users in TV spectrum (UHF and VHF bands) [2]. This concept can be extended to other licensed user systems and is popularly called as the Cognitive Radio (CR) technology [3]. A wireless network designed based on the CR technology is referred to as a cognitive radio network (CRN). A CRN is composed of two types of users, namely, the primary users (licensed users) and the secondary users (unlicensed users). The primary users have a higher priority than the secondary users in accessing the channels in the licensed spectrum. In most cases, the secondary users in a CRN logically divide the channels allocated to the primary users into slots [4]. Within each slot the secondary user has to sense the primary user activity for a short duration and accordingly accesses the slot when it is sensed idle. The idle slots are also called spectrum holes or white spaces. Thus the secondary users can access the licensed spectrum without causing any harmful interference to the primary users

To minimize the interference to the primary users, the secondary users need a reliable spectrum sensing mechanism. Several spectrum sensing mechanisms were proposed in literature [5], [6], [7], in some of which the secondary users are assumed to be able to sense the full spectrum. However, the secondary users usually sense only a part of the spectrum in a slot due to hardware constraints. On the other hand, the secondary users may want to conserve their sensing energy by avoiding the busy portions of the spectrum during sensing. To let the secondary users efficiently manage the sensing mechanism, channel1 status prediction becomes important. The secondary users may predict the status of a channel based on the sensing history and sense only if a channel is predicted to be idle in the next time slot. Thereby, the secondary users can save the sensing energy. Besides, using spectrum prediction, the effective bandwidth in the next slot may be estimated which allows the secondary users to adjust the data rates in advance.

Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding by building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency stimuli by making corresponding changes in certain operating parameters in real time, with two primary objectives: highly reliable communications whenever and wherever needed and efficient utilization of radio spectrum.

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A number of different methods [8] are proposed for identifying the presence of signal transmissions. In some approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the signal type. In [9], the spectrum prediction was done using a linear filter model followed by a sigmoid transform. The performance of the predictor suffered due to the non-deterministic nature of the binary series. In [10], a hidden Markov model (HMM) based spectrum predictor was proposed. The primary user traffic follows Poisson process with 50% traffic intensity (i.e., 50% channel time is occupied by the primary users). However, in [10] the accuracy of channel status prediction was not provided. Another HMM based predictor was also proposed in [11], but it only deals with deterministic traffic scenarios, making it not applicable for the actual environment. There are several drawbacks in using the HMM based spectrum prediction schemes [10], [11] such as, determining an optimal model (number of states in the HMM) is difficult and even impossible in practice, a huge memory space is needed to store a large number of past observations, and model estimation has high computational complexity.

This paper contributes in this direction, to build a spectrum predictor model using soft computing, towards discovering spectrums which will remain idle in a Cognitive Radio system. The predictor scheme relies on artificial neural networks supervised algorithms and aims at solving the problems related to the channel estimation and predictive modeling phase of cognitive radio systems .The proposed scheme can facilitate the cognitive terminal in making the best decision regarding the configuration in which it should operate. The performance assessment work that needs to be conducted in order to design and use an appropriate neural network structure is also described in the paper.

II. PROPOSED METHODOLOGY

The MLP network is a multilayered structure consisting of an input layer, an output layer, and a few hidden layers. Excluding the input layer, every layer contains a certain number of computing units (referred to as neurons) which calculate a weighted sum of the inputs and perform a nonlinear transform on the sum. The nonlinear transform is implemented using a hyperbolic tangent function. Neurons belonging to different layers are connected through adaptive weights. The number of hidden layers and the number of neurons in each layer depend on the application.

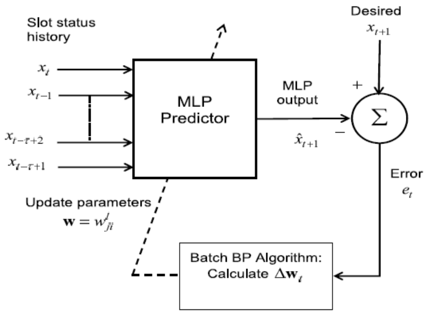

Fig 1: MLP Process

The MLP predictor training process is illustrated in above figure. The parameters of the MLP predictor are updated using the batch back propagation (BP) algorithm. The training patterns are obtained by ordering the entire binary series x^T_1 into input vectors $x^t_{t-\tau+1} = \{x_t, x_{t-1}, \ldots\ldots, x_{t-\tau+2}, x_{t-\tau+1}\}$ of length τ and the corresponding desired value x_{t+1}. For each input vector presented to the input layer of the MLP, the outputs of the neurons in each layer are calculated proceeding from the first hidden layer to the output layer. This computation is called forward pass. The output of the neuron in the output layer y_o^1 is referred to as the MLP output and is denoted by $\hat{x}_{t+1}$. It is treated as an estimate of the corresponding desired value x_{t+1}. The difference between the desired value and its estimate is called as the error e_t which can be expressed as follows:

$e_t = x_{t+1} - \hat{x}_{t+1} = x_{t+1} - y_o^1$

The objective of the training algorithm is to minimize this error e_t by adapting the parameters w^l_{ji} such that the MLP output approximately represents the desired value. In other words, the MLP predictor tries to create a mapping function between the input vector and the desired value. According to the BP algorithm, it is easier to minimize a mean square error criterion E (= ½ $\sum e_t^2$) than to directly minimize the error e_t. Based on the BP algorithm, the parameters are updated as follows:

$w_t = w_{t-1} - \Delta w_t$ …………. (1)

$\Delta w_t = -\eta(\partial E/\partial w_t) + \beta\Delta w_{t-1}$ …………(2)

In equations (1) and (2), w_t represents the parameter w^l_{ji} at time instant t while η and β represent the learning rate and the momentum term respectively and η can be chosen from the range (0, 1) while β can be chosen from the range [0.5, 0.9].

The following steps give the methodology to be used for the proposed work which is Error Backpropagation Training Algorithm (EBPTA):-

Given are P training pairs $\{z_1, d_1, z_2, d_2, \ldots, z_p, d_p\}$,where z_i is $(l \times 1)$, d_i is $(K \times 1)$, and i = 1, 2, ..., P. The l^{th} component of each z_i is of value -1 since input vectors are augmented. Size J - 1 of the hidden layer having outputs y is selected. J^{th} component of y is -1, since hidden layer have also been augmented. y is $(J \times 1)$ and o is $(K \times 1)$. In the following, q is training step and p is step counter within training cycle.

Step 1: Choose $\eta > 0$; $Emax > 0$. Initialized weights at small random values, W is $(K \times J)$, V is $(J \times I)$. Initialize counters and error: $q \leftarrow 1, p \leftarrow 1, E \leftarrow 0$

Step 2: Input is presented and the layers output is computed. Set $z \leftarrow z_p$, $d \leftarrow d_p$, $y_j \leftarrow f(v_j^t z)$, j = 1, ..., J where v_j a column vector, j^{th} row of V . $o_k \leftarrow f(w_k^t y)$, k =1, ..., K where w_k a column vector, k^{th} row of W

Step 3: Error Value is computed. $E \leftarrow 1/2(d_k - o_k)^2 + E$ for k = 1,2 ..... ,K

Step 4: Error signal vectors δ_o and δ_y of both layers are computed. The error signal terms of the output layer in this step are $\delta_{ok} = 1/2\,(d_k - o_k)^2(1 - o^2_k)$, for k = 1, ... K

The error signal terms of the output layer in this step are

$$\delta_{yj} = 1/2\,(1 - y^2_j)\sum_{k=1}^{K} \delta_{ok}\, w_{kj} \text{ for } j = 1, \ldots, J$$

Step 5: Output layer weights are adjusted. $w_{kj} \leftarrow w_{kj} + \eta\delta_{ok}y_j$; k = 1, 2,…K j = 1,2,…J

Step 6: Hidden layer weights are adjusted. $v_{ji} \leftarrow v_{ji} + \eta\delta_{yj}\, z_i$; *j = 1,2,….J and i = 1,2,… I*

Step 7: If $p < p$ then $p \leftarrow p + 1$; $q \leftarrow q + 1$ and go to step 2; otherwise go to step 8.

Step 8: The training cycle is completed.

For $E < E$max, terminate the training output weights *W*, *V*, *q* and *E*.

. If $E > E$max, then $E \leftarrow 0$, $p \leftarrow 1$, and initiate the new training cycle by going to step 2.

III. SIMULATIONS AND RESULTS

The best training procedure is to compile a wide range of examples (for more complex problems, more examples are required), which exhibit all the different characteristics of the problem. To create a robust and reliable network, in some cases, some noise or other randomness is added to the training data to get the network familiarized with noise and natural variability in real data. Poor training data inevitably leads to an unreliable and unpredictable network. Usually, the network is trained for a prefixed number of epochs or when the output error decreases below a particular error threshold. Special care is to be taken not to over train the network. By overtraining, the network may become too adapted in learning the samples from the training set, and thus may be unable to accurately classify samples outside of the training set.

Choosing the initial weights:

The number of hidden neurons affects how well the network is able to separate the data. A large number of hidden neurons will ensure correct learning, and the network is able to correctly predict the data it has been trained on, but its performance on new data, its ability to generalize, is compromised. With too few hidden neurons, the network may be unable to learn the relationships amongst the data and the error will fail to fall below an acceptable level. Thus, selection of the number of hidden neurons is a crucial decision.

Choosing the number of neurons:-

The learning algorithm uses a steepest descent technique, which rolls straight downhill in weight space until the first valley is reached. This makes the choice of initial starting point in the multidimensional weight space critical. However, there are no recommended rules for this selection except trying several different starting weight values to see if the network results are improved.

Choosing the learning rate:-

Learning rate effectively controls the size of the step that is taken in multidimensional weight space when each weight is modified. If the selected learning rate is too large, then the local minimum may be overstepped constantly, resulting in oscillations and slow convergence to the lower error state. If the learning rate is too low, the number of iterations required may be too large, resulting in slow performance. We have built spectrum predictor model capable of identifying white spaces or spectrum holes.

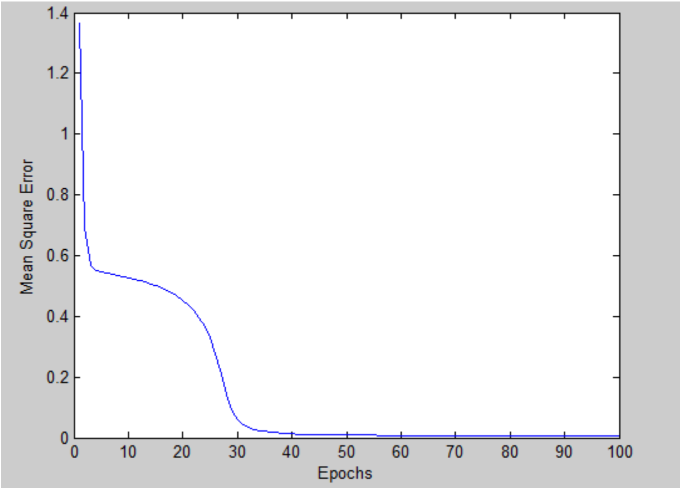

Fig 2: Plot of MSE Vs Epochs

Above Fig shows that after 55 epochs, the amount of mean squared error generated is less than its predefined maximum value and ANN is said to be trained properly.

IV. CONCLUSION

Spectrum is a very valuable resource in wireless communication systems, and it has been a focal point for research and development efforts over the last several years. Cognitive radio, which is one of the efforts to utilize the available spectrum more efficiently through opportunistic spectrum usage, has become an exciting and promising concept. Channel status prediction in cognitive radio networks can not only save the sensing energy greatly, but also improve spectrum utilization. As the statistics of channel usage by primary users in cognitive radio networks is not known a priori, we have designed the channel status predictor using the neural network model, multilayer perceptron (MLP). Performance of the Error Back propagation Training Algorithm (EBPTA) is improved by applying all possible set of training inputs so that there will occur very less amount of mean squared error.

However, cognitive radio is still in its infancy. Development of cognitive radio systems are cross related and dependent to developments in many different technical and non-technical areas like: software defined radio, digital signal processing, artificial intelligence and machine learning, but also bio-inspired intelligence, social group behavior, economical studies, etc. Emergence of full cognitive radio capable radio system is still years, even decades far away from practical realization. What we currently see is: many research advances in the area and gradual implementation of various cognitive radio related technological concepts in modern communication systems. Even if only thirty percent of predicted cognitive radio system functionalities will be realized in radio devices in the forthcoming years, this would bring significant advances to future wireless communications systems.

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