Spectrum Availability Prediction for Cognitive Radio Networks

K.Annapurna, T.Hymavathi, B.Seetha Ramanjaneyulu

Abstract— Cognitive radio networks enable the secondary users to make use of the frequency spectrum of primary users in the absence of the latter. To make this mechanism possible, secondary users have to sense the spectrum to find vacant channels to occupy them as well as to vacate the occupied channels when their primary users come back. ANFIS based spectrum prediction is proposed in this work to improve the spectrum utilization, reduce interference to primary users, enhance quality of service to secondary users and save sensing energy and time. Comparison of predicted data with actual data shows that the predicted occupancy of spectrum is close to the actual occupancy.

Keywords— Spectrum Prediction, ANFIS, Cognitive Radio Networks, Opportunistic Channel Access.

I. INTRODUCTION

Day to day usage of wireless communications is increasing rapidly due to information sharing in the form of videos, images and the like. In the case of wired communications, the existing bandwidth in a region can be increased by laying more number of cables. But it is not possible with wireless communications, because the same spectrum of air environment has to offer support to the additional communication demands. Hence the increased usage willy lead to interference.

In many countries, the available wireless frequency spectrum was already assigned to various applications like television, navigation, mobile communications, military communications etc by the respective governments of the countries. These allocated frequencies are called licensed frequencies. According to FCC (Federal Corporation Commission) of USA, the licensed frequencies are not being utilized up to 30% even [1].

On the other hand, some frequencies are available unlicensed usage for industrial, scientific and medical applications. These are called ISM (Industrial, Scientific and Medical) bands. The ISM bands can be freely utilized by unlicensed users, but they became crowded due to the increased number of such unlicensed devices.

Cognitive radio technology was proposed to solve the spectrum scarcity problem of new users by making use of the under-utilized frequencies of licensed users.

Cognitive Radio is an intelligent transceiver (transmitter/ receiver) which can sense the unused portions of the licensed spectrum and change its transmission or reception parameters to make use of those available spectrum channels for its own communication [2] - [5]. In this technology, licensed users are called primary users (PUs) and unlicensed users are called secondary users (SUs).

Though the availability of vacant spectrum (called as spectrum holes, in this context) varies from time to time, and from location to location, it can be expected that some pattern can be observed in their prevalence. If this pattern can be known in advance, it may be possible to plan accordingly, to use these vacant channels in an efficient manner. Spectrum prediction techniques can help in realizing this objective. In overlay type of spectrum sharing, after acquiring the channel, the secondary users need to sense the spectrum periodically to detect the reappearance of primary users. For this spectrum sensing, it requires considerable amount of time, which results in the reduction of the time duration available for transmissions of secondary users.

By incorporating prediction into the system, SUs will sense only those channels which are predicted to be free, instead of sensing all channels, which saves time and energy. However, to support the unexpected re-entries of the PUs, some mechanisms like the message passing through control channels will be needed. The various sensing mechanisms and its challenges are presented in the following section, which is followed by the prediction mechanisms.

By making use of the spectrum prediction information, the SUs will have a fair idea of spectrum occupancy with respect to time. The details of how many free channels will be available, whether is it better to participate in the competition or not, can be known in advance. This knowledge will be helpful in proper planning of spectrum holes usage so as to avoid many spectrum handoffs. Spectrum prediction not only supports the secondary users to plan their transmissions, but also reduces the interference caused to primary users when they reappear.

In this work, a method called Adaptive Neuro Fuzzy Inference System (ANFIS) that makes use of Neural networks and Fuzzy logic, is used to predict the vacant channels status in advance. Based on this prediction, SUs can plan to avail a channel when it is relatively free. It also enables the SUs to vacate the channel quickly whenever PU comes back, which results in reduced interference to PUs. The performance of prediction is measured in terms of mean square error (MSE) with respect to number of samples used for training of data pertaining to spectrum occupancy of earlier days and months.

Revised Manuscript Received on April 11, 2019.

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II. RELATED WORK FROM LITERATURE

One of the challenging problems of cognitive radio networks is Spectrum prediction which involves several sub topics such as PU transmitter detection, channel status prediction, PU receiver detection, PU activity prediction, transmission rate prediction and radio environment prediction [6] - [7].

Cognitive radio networks make use of different learning mechanisms ranging from pure lookup tables to complex machine learning techniques such as evolutionary/genetic algorithms, artificial neural networks, hidden Markov models, and reinforcement learning [8].

In [9], the authors proposed two different ways of channel status predictions. One is neural network based multi layer perceptron and second is hidden Markov model. The benefit of these two predictors is they do not require any prior information of the channels.

In [10] the authors proposed four different spectrum prediction schemes to anticipate the future inactive times of channels and to select a channel having longest spectrum holes so that they need not face spectrum handoffs. All the four are related to supervised learning and they are ANN based multi layer perceptron, ANN based recurrent neural networks, support vector machine based Gaussian kernel and support vector machine based linear kernel.

In [11] hidden Markov model based prediction is employed to predict the activity patterns of the channels. They considered slow, balanced and heavy traffic scenarios for checking their prediction results.

The authors of [12] proposed a simple prediction scheme based on Bayesian theorem and compared the results with exponential moving average (EWMA) based approach. They suggested a modified EWMA based approach by incorporating the Bayesian theorem. It is found that the computational complexity is less for Bayesian approach.

In [13], cooperative prediction is proposed which is based on game theory. The authors have proved that the cooperative prediction is more efficient than individual prediction.

The prediction proposed in this work is a simple ANFIS based prediction, which is less complex, compared to the above works. As it does not need any deep learning mechanisms, it can be incorporated easily at user level devices with less hardware and software configurations. ANFIS combines the mathematical properties of artificial neural networks and rule based fuzzy inference system, which mimics the human's approach to have the advantages of both.

III. ANFIS

Fuzzy Inference System (FIS) is capable of defeating the drawbacks of a conventional forecasting method i.e. ARIMA (Auto Regressive Integrated Moving Average), because fuzzy inference system is capable of interpreting knowledge from experts as well as historical data in the form of rules. But the drawback of FIS lies in not providing an accurate prediction for cyclic data. The solution to this problem is to add Neural Networks (NN) based prediction to it. Neural Network has the capability of predicting non-linear variables with negligible errors, but the problem is that it needs longer times for training of the neural network. So combination of neural networks and FIS, that is Adaptive Neuro-Fuzzy Inference System (ANFIS) will solve both the problems of inaccuracy and high training time requirement.

In this work, ANFIS based PU activity predictor model is proposed to support the secondary users of cognitive radio networks. This will help to construct a more accurate prediction model with less complexity. Artificial Neural Networks are made up of artificial neurons interconnected to each other to form a programming model that imitates the activities and neural processing of biological neurons. Biological neural networks are nothing but human nervous system, which is made up of interconnection of biological neurons, particularly human brain. Human brain has the capability of parallel data processing and hence can perform tasks much faster than computer.

In the applications of information theory fuzzy logic plays an important responsibility while making decisions in dealing with random issues. Because of this advantage, fuzzy sets got popularity in so many upcoming applications like image processing, pattern recognition, prediction, diagnostics, production engineering and so on. ANFIS combines the mathematical properties of artificial neural networks and rules based fuzzy inference system, which mimics the human's approach to have the advantages of both. It is proved that ANFIS is giving satisfactory results for non-linear functions also. In ANFIS the parameters of the membership functions are obtained from the original data, which gives the system behavior. It adjusts the system parameters by learning data features for the specified error [14]. Because of hybrid approach it is not much dependent on human intervention and is more useful in making ANFIS models.

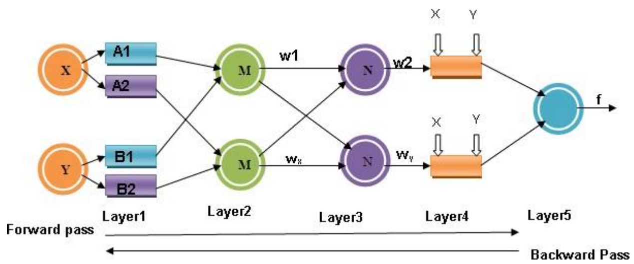

Fig 1. ANFIS Architecture

Forward pass

The ANFIS architecture is described in Fig.1 which uses two inputs and one output. It contains five layers. Fuzzification is done on first layer, which maps the inputs into fuzzy sets of appropriate classification. To convert the raw data into some classification groups, membership functions of the fuzzy logic are used. Generalized Bell (G–Bell) membership function is used in this work considering the important parameters mean and standard deviation.

The inference engine process is carried out in second and third layers to decide the fuzzy rule for the next processing steps. Normalization of nodes is done at third layer. Defuzzification, the conversion of fuzzy information into raw data is done on the fourth layer. LSE is calculated on

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this layer to get next parameter ratio. Next calculation is done on fifth layer. The first, second, third and fourth layers are fuzzy in ANFIS and part of hidden node of the neural networks.

Backward pass

The back propagation algorithm (EBP) is carried out in the backward pass to update the 'a' and 'c' ratios based on calculated error. The systematic backward run can be observed in Fig.1.

IV. MODEL AND DESCRIPTION OF PREDICTION

A. Model

In this system two similar data sets are used, one for checking and the other for training, explains the usage of the ANFIS editor Graphical User Interface (GUI) with checking data to minimize the effect of model over-fitting.

By using uniform distribution of PU occupancy with maximum conference time of 60 minutes and assigning a maximum frequency of PU arrivals as 20 in various channels is observed.

For 15 channels PU's occupancy, probability is predicted by using ANFIS method. Here the FIS output, Training Error, RMSE (Root Mean Square Error), ANFIS output and prediction errors are observed. The concept is based on the prediction of PUs occupancy for various available vacant channels in the spectrum that can be utilized properly.

B. Description of Prediction

The training and checking data are loaded into workspace. Training data is a set of data used to identify the predictive relationship. Test set is used to estimate the power of derived predictive relationship. Training Data is taken from PUs occupancy probability for one day that is 24*60=1440 minutes.

The model starts over-fitting after some time during training. To overcome this problem and to set the parameters, checking data set is used. Now this data is helpful in training fuzzy system by adjusting the parameters of membership functions, such that the parameters become the best suitable to represent the data.

Next it needs to specify initial fuzzy inference system ANFIS as shown in Fig.2.

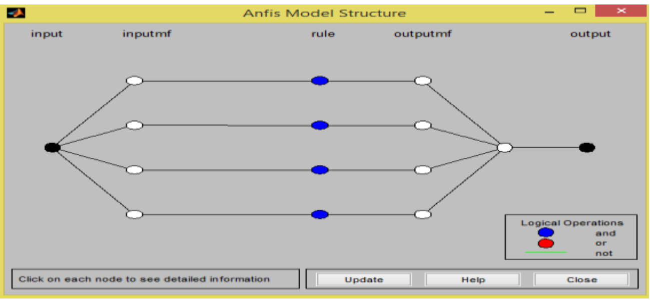

Fig.2. Generation of FIS information structure

The requirement of fuzzification is to map the inputs from a set of sensors to numbers from 0 to 1 by using a set of input membership functions. The Concept of AND is used to prepare the fuzzy rule. Four G-membership functions are considered in this work. The main general task of any prediction, machine learning etc. is to fit a model for a set of training data, so as to guarantee trustworthy predictions to predict any general raw data. A statistical model results in noise or random error instead of forming proper relationship in over fitting.

V. RESULTS AND DISCUSSION

Out of 15 channels, the probability of PU's cumulative activity for one channel is shown in Fig 3. Training errors for training data and checking data are shown in Figs 4 and 5 and in Table -1.

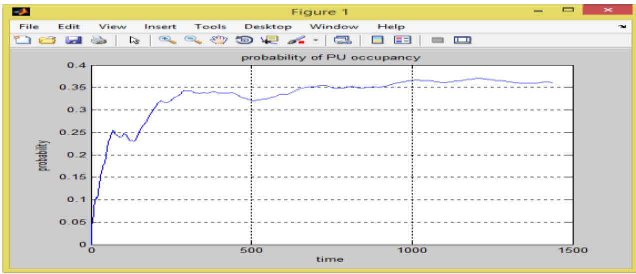

Fig.3. PU's cumulative occupancy probability for a channel in a day

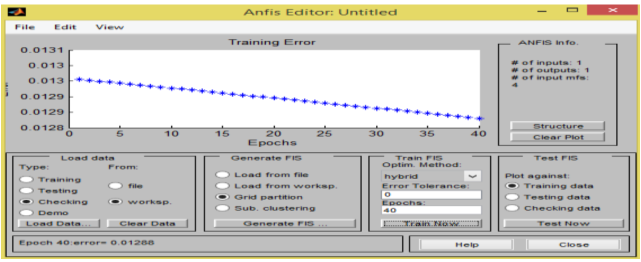

Fig.4. Training error for training data

From figs 4 and 5 it is observed that the maximum training error for both training data and checking data is 0.013 and is decreasing as the number of epochs increase.

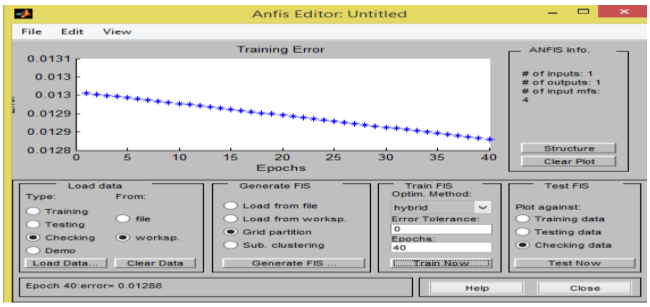

Figure 5. Training error for checking data

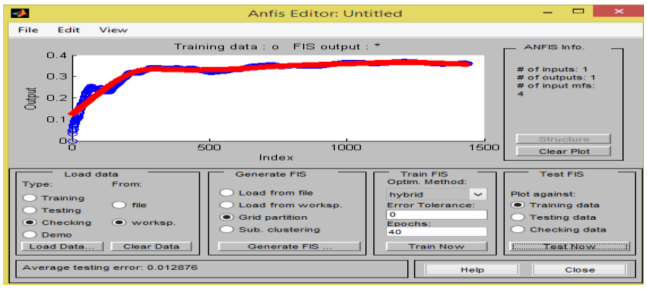

Figure 6. FIS output for training data

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Table 4-1. Training error for training and checking data

Type of Data	Number Of Epoches	Error
Training Data	40	0.1266
Checking Data	40	0.1255

Genfis, fuzzy inference system (FIS) produces the output surface for the FIS, by drawing the first output variable aligned with the first two input variables. If a fuzzy system has more than two inputs then the leftover inputs will use their middle value as reference. Figs 6 and 7 shows the FIS output for training data and checking data. It is noticed that the FIS output in red color is following the actual data, which is in blue color.

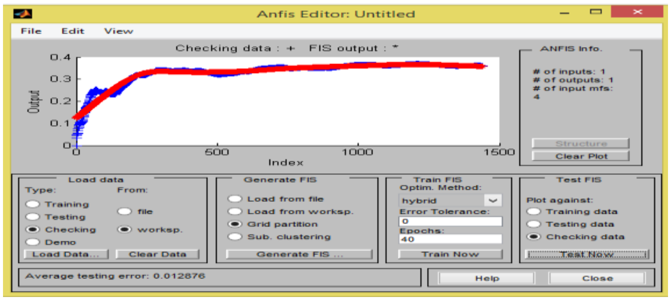

Fig.7. FIS output for checking data

The most frequently used metric for prediction is Root Mean Square Error, which computes the difference between actual values and predicted values. The RMSE for training and checking data is shown in Fig.8. The plot displays RMSE. It is observed that RMSE of training data is very less compared to the checking data.

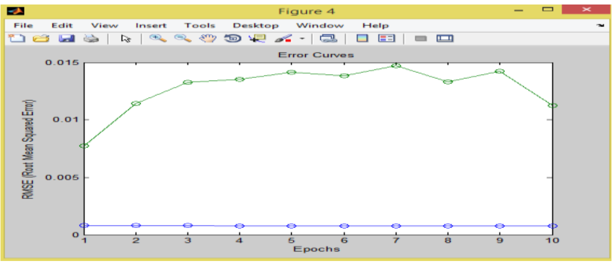

Fig.8. Root-Mean-Square Error for training and checking data

Finally, the prediction output and error using ANFIS are shown in Fig.9. The average error is almost negligible.

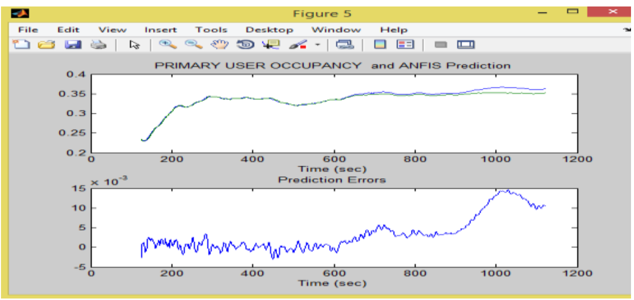

Fig.9. ANFIS prediction output and Prediction Errors

VI. CONCLUSION

Spectrum availability prediction using ANFIS based approach is carried out in this work. Prediction results are comparable with the actual vacant channels information that is available from time to time. The uniform distribution of PU occupancy scenarios are considered for training data.

With this type of prediction, secondary users can plan in advance to improve their blocking and dropping probabilities. Interference to primary users during spectrum handoff can be reduced. It also helps in saving the energy and time spent by secondary devices towards spectrum sensing. It also results in effective utilization of bandwidth. From the results, it is observed that higher levels of training offer prediction of about 90 percent accuracy.

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