Performance of Cognitive Radio Using Adaptive Neural Fuzzy Inference System

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Abstract— Over the last several years the world of wireless communications has undergone some critical changes, which have brought it at the front position of international research and development interest, finally resulting in the introduction of a huge number of innovative technologies and associated products such as WiFi, WiMax, 802.20, 802.22, wireless mesh networks and software defined radio. Cognitive radio system uses a base of software defined radio technology and makes use of intelligent software packages that enhance their transceivers with the extremely smart properties of self-responsiveness, flexibility and ability to learn. A cognitive radio system has the capability to change its operating parameters, monitor the results and, finally take actions, that is to say, decide to operate in a specific radio configuration (i.e. radio access technology, carrier frequency, modulation type, etc.), expecting to move the radio toward some optimized operational state. For such a process, learning mechanisms which are competent to exploit measurements are sensed from the environment, gather experience and store knowledge, assess for taking decisions and actions. A cognitive radio system assures to handle this condition by utilizing intelligent software packages that improve their transceiver with radio–responsiveness, ability and flexibility to learn. This paper introduces and assesses learning schemes which are based on artificial neural networks and can be used for predicting the capabilities (e.g. throughput) which can be achieved by a specific radio configuration.

I. INTRODUCTION

An important engineering challenge in today’s wireless communications domain is the proper management of the electromagnetic radio spectrum, which is a valuable yet natural resource. The need for developing efficient spectrum management schemes, capable of exploiting the underutilized frequency bands needs the current static assignment of the radio spectrum in combination with the often criticized governments’ overregulation, and underutilization situations [1,2]. It is therefore a challenge to find underutilization of the radio spectrum, including Federal Communications Commission (FCC) in the United States, TRAI of India. Cognitive radio offers the promise of intelligent radios that can learn from and adapt to their environment and solve spectrum underutilization problems. There are twofold objective used for sensing the radio environment : (i) Identifying those radio spectrum sub bands which are Underutilized by the primary users and (ii) making those bands available for use by unserviced secondary users. With an aim to achieve above ability, cognitive radio determine their behavior in a reactive or proactive manner, based on the external, environmental stimuli, as well as their capabilities, principles, goals, experience and knowledge. The term radio configuration refers to a chosen carrier frequency and a specific radio access technology (RAT) and it can be extended to include other operating parameters like modulation type, transmit power, etc. Joseph Mitola defined the term Cognitive Radio in the year 1999 [3] as “A radio or system that senses, and is aware of, its operational environment and can dynamically and autonomously adjust its radio operating parameters accordingly.” Cognitive radio should be equipped with the ability of learning [4]. Some kind of behavior is exhibited on receiving certain environmental input, systems. If the system changes its behavior over time in order to improve its performance at a certain task, it is called to learn from its interaction with its environment.
The first stage is sensing of radio environment, in this different configurations are found, and the respective environment conditions, e.g. interference related, are sensed. The second stage is prediction and estimation modeling, in this stage the performance capabilities of configurations are discovered (discovery process) and checked, based on the measurements of the previous phase; past experience and knowledge can be exploited in this phase. The third stage is selection of composition, in this stage the desired signal is sent by transference by the means of “best” radio configuration (modulation, frequency RAT, transmit power, etc.), since it is derived from the information of the previous two phases.

Cognitive radios are capable of lessons and storing them into a knowledge base, from where they can be easily accessed, when required, for future decisions and actions. The reasoning at any given time, looks at the current state and determines which actions executable in that state are resulting in a computationally intensive and time-consuming process. The integration of a learning engine is important specifically for the channel estimation and predictive modeling phase, for improving the stability and reliability of the discovery and evaluation of the configuration capabilities, without depending on the recent measurements. Cognitive radio uses different learning techniques ranging from pure lookup tables to arbitrary combinations of machine learning techniques that include artificial neural networks, evolutionary/genetic algorithms, reinforcement learning, hidden Markov models, etc.

II. AN OVERVIEW OF ANFIS

Biological Neural networks are made up of real biological neurons which are physically connected or functionally-related in the human nervous system and specifically in the human brain. Artificial neural networks (ANN) are made up of artificial neurons interconnected to each other to form a programming structure that mimics the behaviour and neural processing of biological neurons. Human brain can perform various tasks much faster than the fastest existing computer due to its ability in massive parallel data processing. ANFIS means Adaptive Neural Fuzzy Inference System. In this best of neural network and Fuzzy system a recombining together. Fuzzy set theory plays a crucial role in dealing with uncertainty issues while making decisions in information theory applications. Due to this fuzzy sets have a bigger attention and interest in modern information technology, production technique, pattern recognition, data analysis, diagnostics, decision making etc. [6-7]. Artificial neural networks (ANNs) are used by neuro-fuzzy systems harness the power of the two paradigms; fuzzy logic and ANNs, by using the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way humans process information. Due to specific approach in neuro-fuzzy development adaptive neuro-fuzzy inference system (ANFIS), has shown satisfactory results in modeling nonlinear functions. In ANFIS, the membership
function parameters are pulled from a data set that describes the behavior of the system. The features in the data set are learnt by ANFIS and adjusts the system parameters to a given error criterion [6]. The hybrid learning and adaptation systems make the ANFIS modeling more efficient and less dependent on expert knowledge. ANFIS architectures is a combination of both the Sugeno and Tsukamoto fuzzy models. The ANFIS architecture is presented by two IF-THEN rules.

Rule 1:-
If U is R₁ and V is S₁ Then \( f_1 = p_1 u + q_1 v + r_1 \)

Rule 2 :-
If U is R₂ and V is S₂ Then \( f_1 = p_2 u + q_2 v + r_2 \)

ANFIS architecture is shown in fig.3 consisting U and V as inputs and z as the output and \( p_i, q_i, r_i \) are the design parameters these parameters which are determined during the training process. In Fig.3 a circle is represented as a fixed node, while a square is represented as an adaptive node.

There are number of membership functions from which we will apply \( \mu_{R_i(U)} \) and \( \mu_{S_{i-2}(V)} \) for the bell shaped function.

\[
\mu_{R_i}= \frac{1}{1 + \left( \frac{X-C_i}{A_i} \right)^{2b}}
\]

The bell-shaped membership functions are leading by the \( a_i, b_i \) which are the parameters and if the values of the parameter change the bell shape functions changes appropriately. These parameters in this layer are premise parameters.

Layer 2
In this layer, every node is represented by a circle node which is labeled with \( \Pi \). This indicates that they perform as a simple multiplier whose output is the product of all the incoming signals. In this layer each node output called as the firing strength of a rule \( O_i^2 = w_i = \mu_{R_i(U)}\mu_{S_i(V)}, \quad i=1,2 \)

Layer 3
In this layer, every node is represented by a circle node which is labeled with N which calculates the ratio of the firing strengths from the previous layer. The outputs of third layer can be represented as:

\[
O_i^3 = \frac{w_i}{w_1 + w_2} = \frac{W_i}{W} \quad i=1,2
\]

Layer 4
In this layer, every node function is represented by a square node. In this layer is the product of the normalized firing strength and a first-order polynomial is the output of each node in this layer.

\[
O_i^4 = \bar{W}_t f_i = \bar{W}_t (p_i u + q_i v + r_i) \quad i=1,2
\]

Layer 3 output is \( \bar{W}_1 \). The \( p_i, q_i, r_i \) are the parameters sets. These parameters in this layer are consequent parameters.

Layer 5
In this layer, there is only single a circle node which is labeled with \( \Sigma \). This node computes the overall output as summation of all incoming signals. The final output of the ANFIS architecture is represented as:

\[
O_i^5 = \sum_i \bar{W}_t f_i = \left( \frac{\sum_i w_i f_i}{\sum_i w_i} \right)
\]

Conventional ANFIS uses grid partition method to generate FIS. Grid partitioning process reduces the
time-consuming learning process. The performance largely depends upon the definition of the grid. Mostly adaptive fuzzy grid partitioning is used to refine and optimize this process. Grid partition method drawback is that the increase in the number of inputs or membership functions as the input variables increase, due to this performance suffers and which will lead to increase high dimensional problem. Most of the partition methods have the same issue hence it is termed as “curse of dimensionality, “So we won’t use this method. The second method which we will use is Fuzzy-C means (FCM) clustering method to generate the FIS, and fix number of rules by fixing fuzzy centers. In the clustering techniques the data can be organized according to the similarity between the specific data items. In solving problems in the areas of pattern recognition and fuzzy model identification fuzzy clustering plays an important role. This method will overcome the dimensionality problem. This method will give optimized rules and best results.

III. GRID PARTITION METHOD FOR MANUAL TRAINING

<table>
<thead>
<tr>
<th>No. of training data</th>
<th>EPOCHS</th>
<th>RMSE</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>400</td>
<td>500</td>
<td>1.2933</td>
<td>5 minutes</td>
</tr>
<tr>
<td>800</td>
<td>1000</td>
<td>0.4962</td>
<td>10 minutes</td>
</tr>
</tbody>
</table>

Table No.1

The training dataset consists of 1300 datapoints and 200 datapoints will be used for testing. Gaussian membership functions are taken for each input. In Table no. 1 it is seen that when epochs are increased rmse is reduced.

Membership Function

The Membership Function (MF) Editor is used to create, remove, and modify the MFS for a given fuzzy system. On the left side of the diagram is a "variable palette” region that you use to select the current variable by clicking once on one of the displayed boxes. Information about the current variable is displayed in the text region below the palette area. To the right is a plot of all the MFS for the current variable.

Subtractive Clustering for data rate

Scenario 1

<table>
<thead>
<tr>
<th>Samples</th>
<th>RMSE</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>6.49E-08</td>
<td>14.020763 seconds.</td>
</tr>
<tr>
<td>1000</td>
<td>1.51E-08</td>
<td>19.014421 seconds.</td>
</tr>
</tbody>
</table>

Table No.2

The training dataset consists of 1300 datapoints and 200 datapoints will be used for testing.
It is been observed that after training Grid partition and Subtractive clustering the RMSE of Subtractive clustering is reduced.

**Testing 200 points**

<table>
<thead>
<tr>
<th>No. of training data</th>
<th>RMSE</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.39E-09</td>
<td>20.017433 secs.</td>
</tr>
<tr>
<td>200</td>
<td>4.84E-09</td>
<td>136.017267 secs.</td>
</tr>
</tbody>
</table>

Table No.3

After comparison between table no. 2 & 3 it is seen that the rmse in table no.3 is reduced.

IV. CONCLUSION

Wireless communications will be characterized by highly reliable surroundings with multiple RATs exhibiting various features. Other important parameters which will help in predicting best radio configuration can be modulation type, frame rate, and environmental conditions etc. and improving QOS of communication links. Selection of the best radio configuration can be achieved by implementation of learning schemes and the investigation which can helps cognitive radios in the taking decisions. Scenarios and test cases used for the derivation of the suitable NN structures are described, while results for this analysis are presented.. ANFIS can have number of alternatives due to the high flexibility of adaptive networks. According to this paper ANFIS based learning scheme is more precise and include less mathematical complexity as compared to neural network. Our testing error is less than the training error and is expected also that confirms our testing and validation is appropriate. When the number of epochs is increased rmse is reduced. From the above study it is observed that SUB.CLUSTERING is the better than Grid Partition method.

REFERENCES