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ANFIS based data rate prediction for cognitive radio

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Abstract

Intelligence is needed to keep up with the rapid evolution of wireless communications, especially in terms of managing and allocating the scarce, radio spectrum in the highly varying and disparate modern environments. Cognitive radio (CR) systems promise to handle this situation by utilizing intelligent software packages that enrich their transceiver with radio-awareness, adaptability and capability to learn. Its system participates in a continuous process, "the cognition cycle", during which it adjusts its operating parameters, observes the results and, eventually takes actions, that is to say, decides 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. In such a process, learning mechanisms utilize information from measurements sensed from the environment, gathered experience and stored knowledge and guide in decision making. This paper evaluates learning schemes that are based on adaptive neuro-fuzzy inference system (ANFIS) for predicting the capabilities (e.g. data rate) that can be achieved by a specific radio configuration in cognitive radio. While CR is an intelligent emergent technology, where learning schemes are needed to assist in its functioning. On the other side, ANFIS based scheme is one of the good learning artificial intelligence method, that combines best features of neural network and fuzzy logic. Here proposed method is able to assist a cognitive radio system to help in selecting the best one radio configuration to operate in. Performance metric like root mean square error (RMSE), prediction accuracy of ANFIS learning has been used as performance index.

Keywords: Cognitive radio (CR); Adaptive neuro-fuzzy inference system (ANFIS); Data rate; Spectrum

1 Introduction

The federal communications commission (FCC) is responsible for regulation of interstate telecommunication, management and licensing of electromagnetic spectrum within the United States and it enforces requirements on inter-station interference in all radio frequency bands. The license segments to particular users provided in geographic areas. With the recent boom in personal wireless technologies, these unlicensed bands have become crowded with everything from wireless networks to digital cordless phones. To combat the overcrowding, the FCC has been investigating new ways to manage RF resources. With advances in software defined radio (SDR) and cognitive radio (CR), practical ways of doing this are on the horizon. In the early days of communication, there were fixed radios in which the transmitter parameters were fixed and set up by their operators [1]. A SDR is a radio that comprises a transmitter in which the operating parameters including the frequency range, modulation type or maximum radiated or conducted output power can be altered by making a change in software without making any hardware changes. It is used to minimize hardware requirements in cheaper way and reliable solution. But it will not take into account spectrum availability [2]. On the other hand, CR is newer version of SDR in which all the transmitter parameters change like SDR but it will also change the parameters according to the spectrum availability. It does this by sensing the radio environment with a twofold objective that is identifying those sub bands of the radio spectrum that are underutilized by the primary (i.e., legacy) users and providing the means for making those bands available for use by un serviced secondary users[3]. The idea of

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cognitive radio goes beyond making productive use of unused part of the spectrum and being capable of making human-like decisions to transmit without obstruction.

In the more general sense, the term radio configuration or simply configuration refers to a chosen carrier frequency and a specific radio access technology (RAT) but can be extended to include other operating parameters like transmit power, modulation type, etc. This definition also allows a spectrum band to be used for operating in different RATs, in accordance with the flexible spectrum management. The objective of work is to bring in the learning capability in channel estimation and predictive modeling phase for improving the stability and reliability of the discovery and evaluation of the configuration capabilities, without relying solely on the recent measurements. To this effect, different learning techniques are available and can be used by a CR that include artificial neural networks (ANN), ANFIS, evolutionary/genetic algorithms, reinforcement learning, hidden Markov models, etc. In this work, an ANFIS model based technique for data rate prediction in assisting cognitive radio has been proposed. This paper work is organized as section 2 elaborates the cognitive radio and section 3 proposes ANFIS architecture for learning scheme. Moreover, section 4 discusses simulation of model along with last section discusses conclusion and future work to be done.

2 Cognitive radio

The CR does not have the history of a century rather the development of it is still at a research stage. It is an emerging technology, for the efficient use of the limited available spectrum. Nevertheless, as look in to the future that CR has the capacity to make a significant difference to the way the radio spectrum can be accessed, with much improved utilization. Indeed, given its potential, it can justifiably be described as a "disruptive, but unobtrusive technology". Joseph Mitola [3] described the way a CR could enhance the flexibility of personal wireless services, through a new language called the "Radio Knowledge Representation Language" (RKRL). According to Mitola [3], It can defined as "The point in 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, as well as to provide radio resources and wireless services most appropriate to those needs". However, the concept of CR is not limited strictly to wireless devices such as PDAs. Widely cited paper by Simon Haykin defines that it 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 [4]. Moreover, two primary objectives are highly reliable communications and efficient utilization of the radio spectrum. Some of the important applications of CR are improving spectrum utilization & efficiency, improving link reliability, less expensive radios, advanced network topologies, enhancing SDR techniques and automated radio resource management [5]. On the other hand, CR is limited by security, software reliability, keeping up with higher data rates and loss of control. In a typical CR operation is presented as a simplification to the cognition cycle initially described in and can be divided into three, tightly interconnected tasks as depicted in figure 1[6,7]

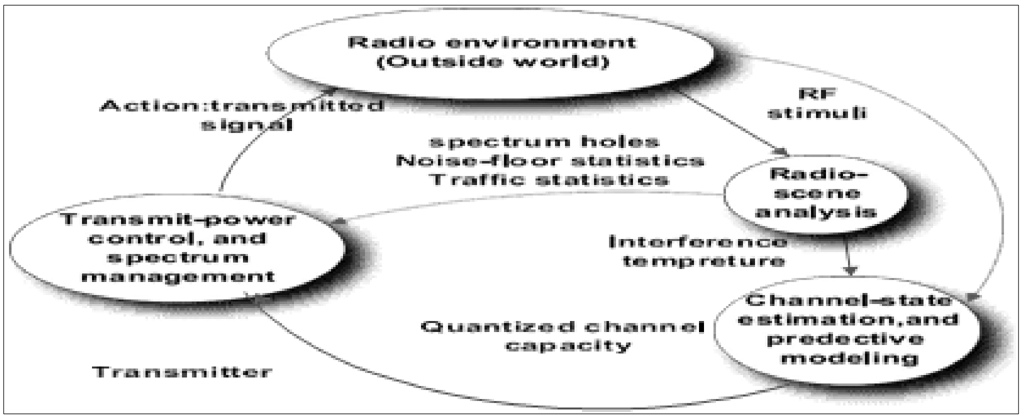

Figure 1 Basic cognitive cycle

During radio scene analysis, different configurations are probed to estimate interference temperature of the radio environment and to detect of spectrum holes. This interference temperature is a measure of the sensed power in a certain frequency band. Thus, by obtaining this measure, a maximum level where any signal exceeds threshold level and a minimum level where any signal below it can be neglected and thus that certain band can be considered as empty or unused, and can be used by other users[8,9]. 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. Primary users are those holding licensed channels or primary bands. Channel estimation was also proposed to be part of the CR. This operation aims in analyzing the channel behavior and its effects on the transmitted signal and estimating the impulse response of the channel[10,11]. The predictive modeling uses the current observations along with the previous observations and based on some statistical measures it tries to find the model that will most likely suits the channel or the traffic in the near future. Usually, prediction implies the possibility for some errors. But it significantly improves the performance of the system to an extent where those errors can be neglected.

3 Problem analysis

The prime objective is to study learning schemes that is based on ANFIS and designed to enhance the capabilities of a cognitive terminal, in terms of assisting it to predict the data rate that a specific radio configuration could achieve if it was selected for operation and at last to give benchmarking on ANFIS networks. The purpose here is to detect and classify the spectrum sensing techniques for CR networks by using signal processing techniques. The sensing has been analyzed for a few identified situations and then these behaviors have been reported to the operator for further action[12,13]. The ultimate objective of the CR is to obtain the best available spectrum. Since there is already a shortage of spectrum, the most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users as illustrated in figure 2.

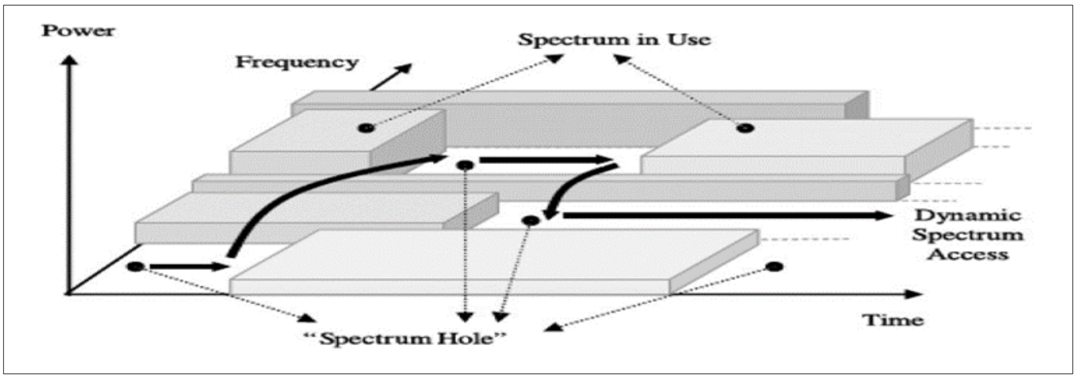

Figure 2 Spectrum Hole

The CR enables the usage of temporally unused spectrum, which is referred to as spectrum hole or white space. If this band is further used by a licensed user, the CR moves to another spectrum hole or stays in the same band, altering its transmission power level or modulation scheme to avoid interference. In spectrum sensing there is a need to find spectrum holes in the radio environment for CR users. However it is difficult for CR to have a direct measurement of channel between primary transmitter and receiver. A CR cannot transmit and detect the radio environment simultaneously, thus, a need such spectrum sensing techniques that take less time for sensing the radio environment. In literature the spectrum sensing techniques have been classified as in figure 3.

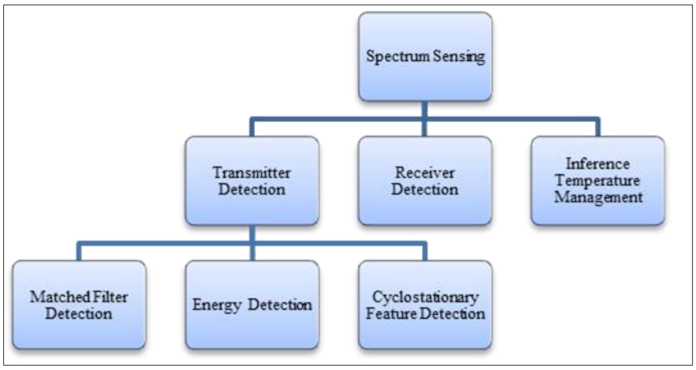

Figure 3 Classification of spectrum sensing techniques

Here, those primary transmitters are identified which can broadcasting at any given time. Based on hypothesis model for transmitter detection the signal received by the secondary user can be

$$x(t) = n(t), H_O \text{.....................}(1)$$

$$x(t) = hs(t) + n\ (t), H_l \text{...........................}(2)$$

Where, H_0 and H_l indicates primary user's absent and present respectively. The CR received signal represent by $x(t)$ while s(t) is the transmitted signal of primary user. The channel parameters $n(t)$ denotes additive white Gaussian noise (AWGN) and amplitude gain correspondingly. On the basis of model, it can be classified in to matched filter, energy and cyclostationary feature detection. A matched filter is a linear filter designed to provide the maximum signal-to noise ratio at its output for a given transmitted waveform. Energy detector measures the energy received from primary user during the observation interval. If energy is less then certain threshold value then it declares it as spectrum hole. If CR is aware of the power of the random Gaussian noise, then energy detector is optimal.

4 System model

Now the spectrum sensing techniques which are able to remove the problems in transmitter detection. To remove receiver's uncertainty, we have to design techniques which we have some information about primary receiver. Then new spectrum sensing techniques are introduced in which we will get information about receiver from its own architecture. Interference is typically regulated in a transmitter centric way. It can be controlled at the transmitter through radiated power, out-of-band emissions, location of individual transmitters and frequencies used by specific type of radio operations. There interference management techniques served well in the past but do not take into account the interference from the receiver point of view, as most of interferences occur at the receiver. Moreover, the dramatic increase in the overall demand for spectrum based services, rapid technical advancements in radio systems; in particular the introduction of new robust modulation techniques demands a new technique that focuses on actual RF environment and interaction between transmitter and receiver. The model is illustrated in below figure 4

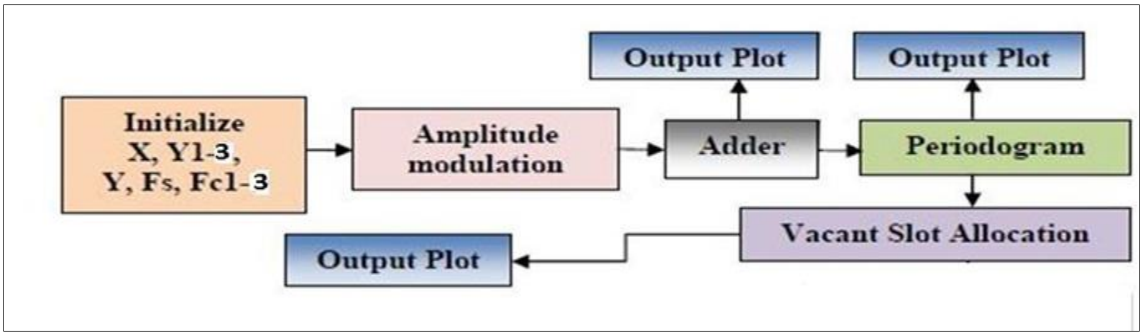

Figure 4 CR implementation

- Initialize- Initializes carrier frequency bands for users and also sampling frequency.
- Modulation- Modulates user data over the respective frequency band using amplitude modulation.
- Adder- Addition of all the modulated signals to produce a carrier signal.
- Periodogram- For estimation of the power spectral density.
- Allocation of unoccupied slot- When a new user arrives he is allotted to the first spectral hole.

Considering a first-order Sugeno fuzzy inference system which contains two rules:

Rule 1: IF X is A1 AND Y is B1, THEN

$$f_1 = p_1 x + q_1 y + r_1 \quad \text{...............}(3)$$

Rule 2: IF X is A2 AND Y is B2, THEN

$$f_2 = p_2 x + q_2 y + r_2 \text{...........................}(4)$$

Figure 5 illustrates graphically the fuzzy reasoning mechanism to derive an output f from a given input vector $[x, y]$ The firing strengths w_1 and w_2 are usually obtained as the product of the membership grades in the premise part, and the output f is the weighted average of each rule's output.

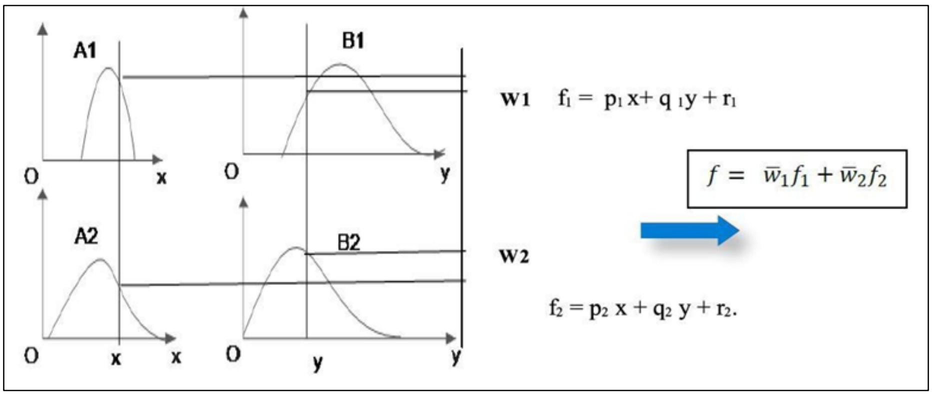

Figure 5 First order Sugeno Model

To facilitate the learning of the Sugeno fuzzy model, it is convenient to put the fuzzy model into framework of adaptive networks that can compute gradient vectors systematically. The resultant network architecture is ANFIS that is shown in Figure 6, where node within the same layer performs functions of the same type, as detailed below. Here circle indicates a fixed node, whereas a square indicates an adaptive node.

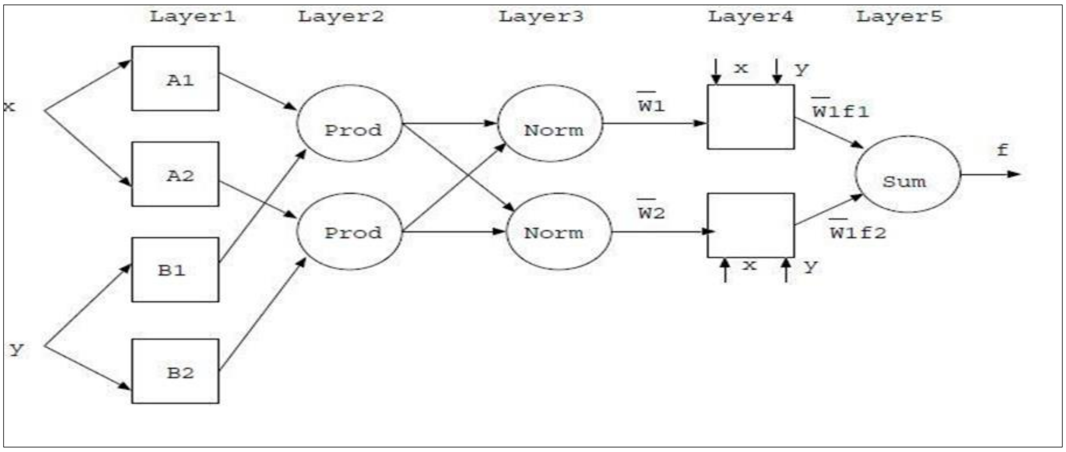

Figure 6 ANFIS Architecture

- **Layer 1:** $\boldsymbol{O_{1,i}}$ is the output of the *i*th node of the layer 1. Every node *i* in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{Ai}(x) \text{ for } i = 1, 2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

$$O_{1,i} = \mu_{Bi-2}(x) \text{for i = 3, 4} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

x or y is the input node i and A_i or B_{i-2} is a linguistic label associated with this node. Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A1, A2, B1, B2). Its typical membership function:

$$\mu_A(x) = \frac{1}{1+\left|x-{}^{c_i}/{}_{a_i}\right|^{2b_i}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where, ai, bi, ci is the parameter set. Parameters are referred to as premise parameters.

- **Layer 2:** Every node in this layer is a fixed node labeled Prod. The output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(x), \text{i} = 1, 2 \ldots\ldots\ldots\ldots\ldots(8)$$

Each node represents the fire strength of the rule. Any other T-norm operator that perform the AND operator can be used

- **Layer 3:** Every node in this layer is a fixed node labeled Norm. The *i*th node calculates the ratio of the ith rule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = w_i = \frac{w_i}{w_1} + w_2, \mathrm{i} = 1, 2 \ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Outputs are called normalized firing strengths.

- **Layer 4:** Every node i in this layer is an adaptive node with a node function:

$$O_{4,1} = w_i f_i = w_i(p_x + q_i y + r_i) \ldots\ldots\ldots(10)$$

w_i is the normalized firing strength from layer 3. $\{p_i, q_i, ri\}$ is the parameter set of this node. These are referred to as consequent parameters.

- **Layer 5:** The single node in this layer is a fixed node labeled sum, which computes the overall output as the summation of all incoming signals, overall output is as follows

$$O_{5,1} = \sum_i w_i f_i = {\sum_i w_i f_i}\Big/{\sum_i w_i} \ldots\ldots\ldots(11)$$

In the ANFIS structure, the parameters of the premises and consequents play the role of weights. Specifically, the shape of membership functions in the "If" part of the rules is determined by a finite number of parameters. These parameters are called premise parameters, whereas the parameters in the "THEN" part of the rules are referred to as consequent parameters. The ANFIS learning algorithm (Jang [12]) consists of adjusting the above set of parameters.

For ANFIS, a mixture of back propagation and least square estimation (LSE) is used. Back propagation is used to learn the premise parameters, and LSE is used to determine the parameters in the rules consequents. A step in the learning procedure has two passes. In the forward pass, node outputs go forward, and the consequent parameters {pi, qi, ri} are estimated by least squares method, while the premise parameters remain fixed. In the backward pass the error signals are propagated backwards, and back propagation is used to modify the premise parameters {ai, bi, ci}, while consequent parameters remain fixed. This combination of least-squares and back propagation methods are used for training FIS membership function parameters to model a given set of input/output data. The performance of this system will be evaluated using RMSE, root mean square errors (difference between the FIS output and the training/testing data output), defined as:

$$RMSE = {1}/{n} \sqrt{\sum_{k=1}^{n} (y_k - o_k)^2} \ldots\ldots\ldots\ldots(12)$$

Where, y_k is the desired output and o_k is the actual system output. n is the number of training/testing samples. In a conventional fuzzy inference system, the number of rules is decided by an expert who is familiar with the target system to be modeled. In ANFIS simulation, however, no expert is available and the number of membership functions (MF's) assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs, visualization techniques are not very effective and most of the time we have to rely on trial and error. This situation is similar to that of neural networks; there is just no simple way to determine in advance the minimal number of hidden units needed to achieve a desired performance level. There are several other techniques for determining the numbers of MFs and rules, such as 54 CART and clustering methods. In a fuzzy inference system, basically there are three types of input space partitioning.

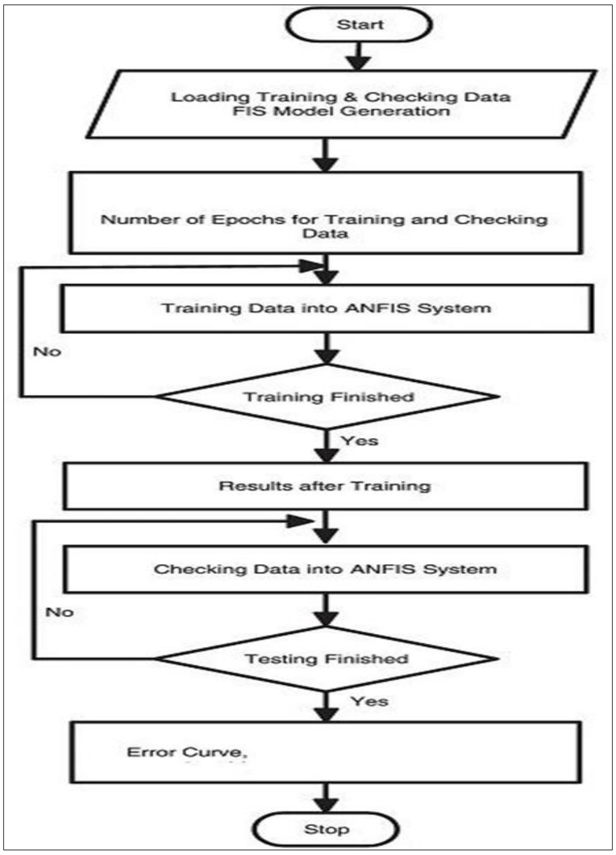

Figure 7 ANFIS design procedure for data rate prediction

5 Simulation

In simulation, three primary users are used in the network having carrier frequency of 1, 2 and 3 KHz along with sampling frequency of 1.2 KHz. Figure 4 shows amplitudes modulated waveform in time-domain while power spectral density illustrated through figure 8.

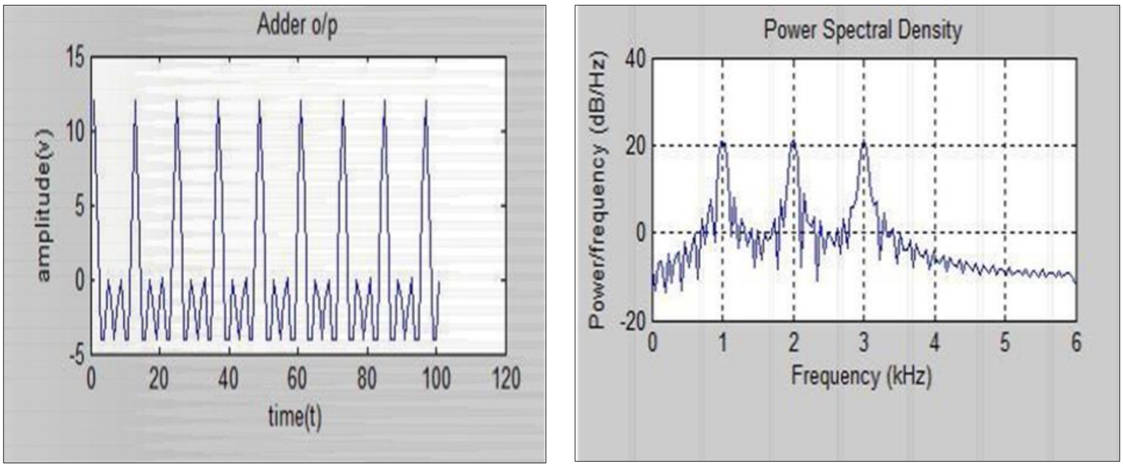

Figure 8 (a) AM time-domain signal (b)Power spectral Density

Here, data is generated from the Mackey glass time delay differential equation which is defined by:

$$\frac{dx}{dt} = 0.2\, x\,(t-\tau)(1 + x\,(t-\tau)^{10}) - 0.1x(t) \quad \ldots\ldots\ldots\ldots(13)$$

When x (0) = 1.2 and r = 17, a non-periodic and non-convergent time series that is very sensitive to initial conditions is generated. (Assume x (t) = 0 when t < 0.)

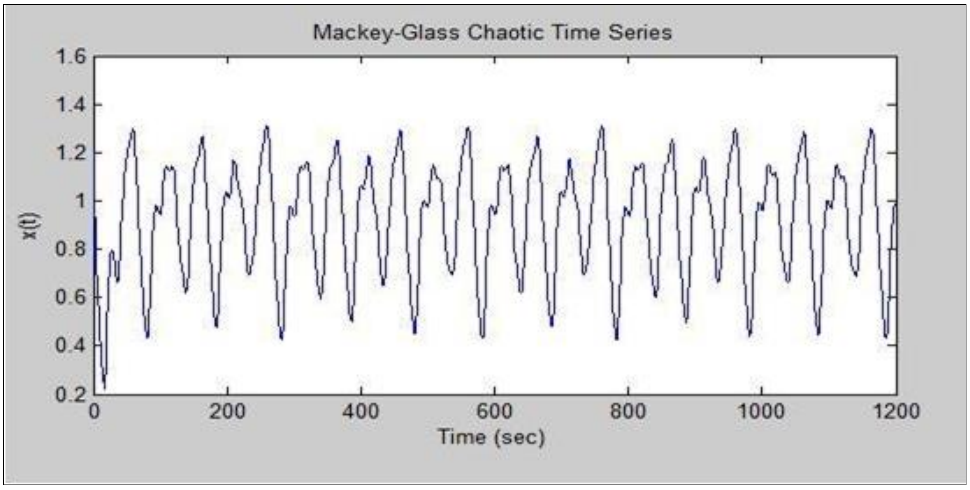

Figure 9 Plot of generation of Mackey-Glass time series data

Now to build an ANFIS structure that can predict x (t + 6) from the past values of this time series i.e., $x\ (t\ -\ 18), x\ (t\ -\ 12), x\ (t\ -\ 6)$, and $x(t)$.Therefore the final training data format is represented as $[x\ (t-\ 18), x\ (t-\ 12), x\ (t-\ 6), x\ (t);\ x\ (t\ +\ 6)]$. From t = 118 to 1117, collect 1000 data pairs of the above format. The first 500 are used for training while the others are used for checking purpose. In figure the plot shows the segment of the time series where data pairs were extracted from. The first 100 data points are ignored to avoid the transient portion of the data.

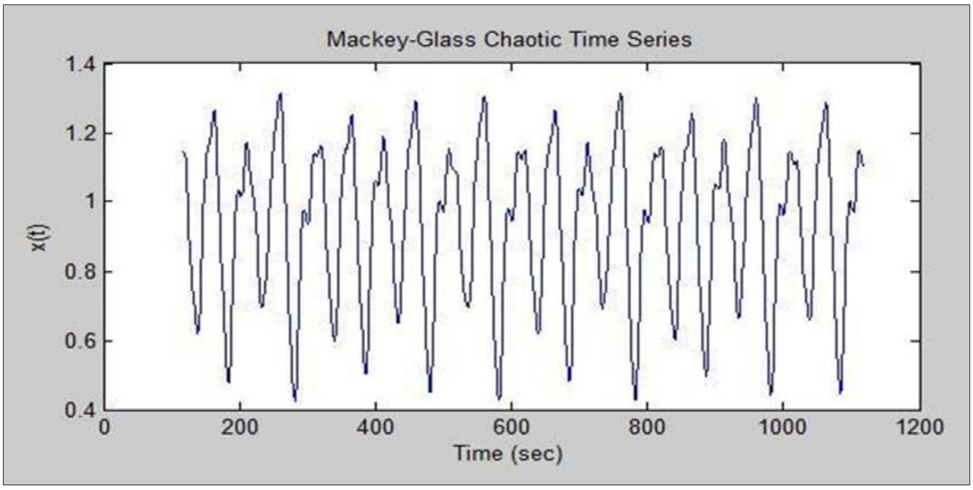

Figure 10 Plot of pre-processing the time series data

There are $2^4\ =\ 16$ rules in the generated FIS matrix and the number of fitting parameters is 108, including 24 nonlinear parameters and 80 linear parameters. This is a proper balance between number of fitting parameters and number of training data (500). Obviously most of the fitting is done by the linear parameters while the nonlinear parameters are mostly for fine tuning for further improvement. This plot displays error curves for both training and checking data. Note that the training error is higher than the checking error. This phenomenon is not uncommon in ANFIS learning or nonlinear regression in general; it could indicate that the training process is not close to finished yet.

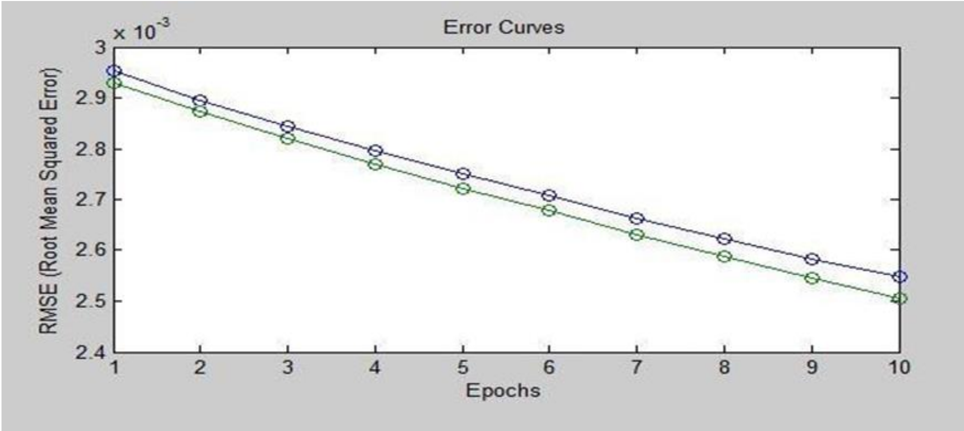

Figure 11 Error curves plot

This plot shows the original time series and the one predicted by ANFIS. The difference is so tiny that it is impossible to tell one from another by eye inspection. That is why you probably see only the ANFIS prediction curve. The prediction errors must be viewed on another scale.

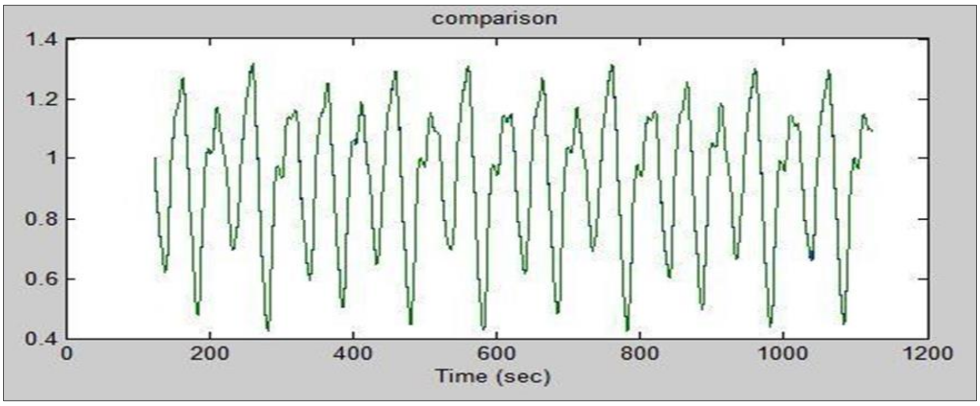

Figure 12 Plot between original time series and the one predicted by ANFIS

Prediction error of ANFIS is shown here. Note that the scale is about a hundredth of the scale of the previous plot. Remember that we have only 10 epochs of training in this case; better performance is expected if we have extensive training.

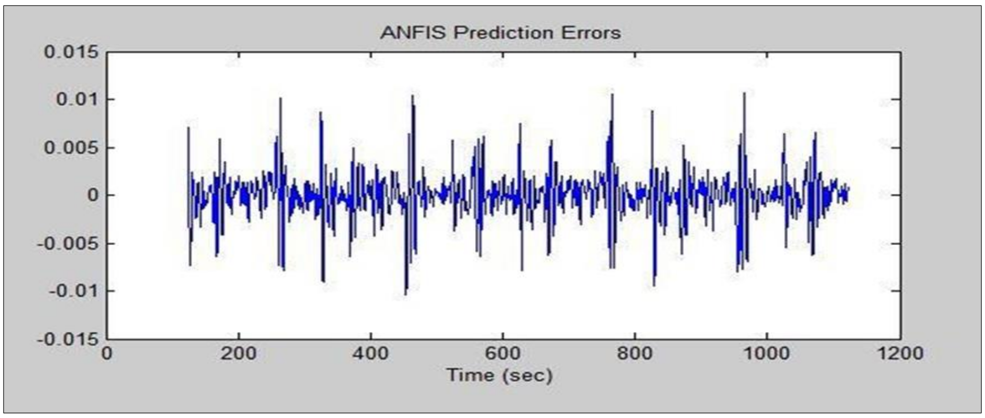

Figure 13 Prediction errors

Hence the original time data series and the one predicted by ANFIS are nearly the same. The difference is so tiny that it is impossible to tell one from another by eye inspection.

6 Conclusion

The main objective of the paper is to assist data rate prediction for CR using ANFIS based learning techniques. This paper uses previous work as reference to implement method. By predicting data rate of particular radio configuration, proposed technique may facilitate the cognitive terminal in making its decision regarding the configuration in which it should operate, selecting the best among a set of candidate ones. The ANFIS based technique works better in accuracy and RMSE error compared to neural network method. But it generated huge rule when number inputs were increased and which could not be handled by simulation environment. The numerical complexity of ANFIS is less than neural network. Methods used in ANFIS generates optimum rules reduces mathematical complexity, where as in neural networks number of nonlinear functions and updating weights are very high compared tunable parameters in ANFIS technique.

- Training and testing of all the models were conducted offline. Since CR is intelligent device so method has to be devised for online process.
- CR complex intelligent radio, so QoS of CR cannot be optimized by only predicting data rate, other parameters like modulation type, frame rate and environment conditions must be considered.
- Proposed method practical applicability has to be verified.

Proposed ANFIS based technique was successful in only prediction of data rate capability of a specific radio configuration. Capability radio configuration not only depends on data rate, it may include different access technology, modulation type, frame rate etc. So ANFIS based technique must be tuned predict all these capability of radio configuration. So for these different types of hybrid ANFIS must be explored. In extended case only time zone parameter is included but practical situation environmental conditions also affect data rate and other radio capabilities. Problem must be formulized to include other parameters which affect data rate. The prediction was based on assumed data series but to validate and check the robustness of ANFIS more realistic scenario must be considered for training. As previously said CR sits on SDR so ANFIS based methods feasibility in hardware implantations must be checked.

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