# ANFIS with Subtractive Clustering-Based Extended Data Rate Prediction for Cognitive Radio

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***Abstract*—Cognitive radio has emerged as intelligent wireless technology for solving the ever-growing demand of radio spectrum.Cognitive radio is a context aware radio, capable of observing the channel and networks parameters and make autonomously decisions on the best transceiver configuration. Cognitive radio can be made adaptive by utilizing intelligent software techniques. In this paper, we propose Subtractive Clustering with ANFIS based adaptive technique so that it works intelligently to select particular radio configuration. The system considers different time zones and subtractive clustering is used to assist ANFIS in selecting optimum number of rules and membership function. The performance of this is seen to be better than the neural network and ANFIS scheme.**

***Keywords- Cognitive radio (CR), spectrumhole, cognition cycle, ANFIS, subtractive clustering, extended scheme***

## I. INTRODUCTION

As it is well known that, spectrum is scarce and very expensive.It is controlled by regulatory bodies like FCC in USA, TRAI in India. In spite of high licensing fees this resource is presently under utilized.It has been found that spectrum bands in the spectrum is unoccupied for some time and many frequency bands in the spectrum are only partially occupied, whereas the remaining frequency bands are heavily used [1]–[4].Problem of under utilization of spectrum has led to use of new adaptive technology called Cognitive Radio (CR). CR attempts to solves problem by sensing the frequency band in license users for free spectrum called *spectrum hole* and allowing spectrum holes to be used by secondary or unlicensed user, without interfering the primary user [3], [4]. For above solution CR has to be intelligent enough to make the decision like human, and to transmit without obstruction and adapt its status according to environmental conditions.

In this work CR considers WLAN terminals as secondary users which behaves intelligently in selecting particular radio configuration by taking into the terminal operation status and environmental conditions. The CR has ability to operate in a particular radio configuration based on device status and environmental aspects including interference noise [1], [5]. In more general sense, the term radio 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 [5]. In this paper we propose learning techniques to be imbibed in channel estimation and predictive modeling phase, which is discussed in section-II. For improving the stability and reliability of the discovery and evaluation of the configuration capabilities, without relying solely on the recent measurements [5], [6]. In this paper we propose ANFIS with Subtractive Clustering (SC) based learning scheme for CR. In our previous work [6], we have proposed simple ANFIS based prediction and compared its performance with neural network based techniques of [5]. As a further improvement,we have considered enhanced test conditions here.In this we reduce the fuzzy rules and membership function of ANFIS by using subtractive clustering technique and also enhance test condition by introducing zones within a day as similar to [5].The performance of the SC-ANFIS assisted CR is compared with variant Neural networks based learning methods checked [5], [6].

Following this introduction the remaining part of the paper is organized as under. Section II, provides an overview of cognitive radio and motivation for the work. Section III, describes overview of subtractive clustering (SC) with ANFIS and its architecture. Section IV presents the simulation model for extended data rate prediction. Results and discussion is presented in section V.

## II. COGNITIVE RADIO-AN OVERVIEW

Cognitive Radio was first introduced by Joseph Mitola [2]in his research work on reconfigurable Radios called SDR in 1999 [1], [2], [4], [5]. The term, cognitive radio, is formally defined by Hykin [1]:as CR is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations to the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- Highly reliable communications whenever and wherever needed
- Efficient utilization of the radio spectrum.

From above definition cognitive capability includes following keywords: awareness, intelligence, learning, adaptability,

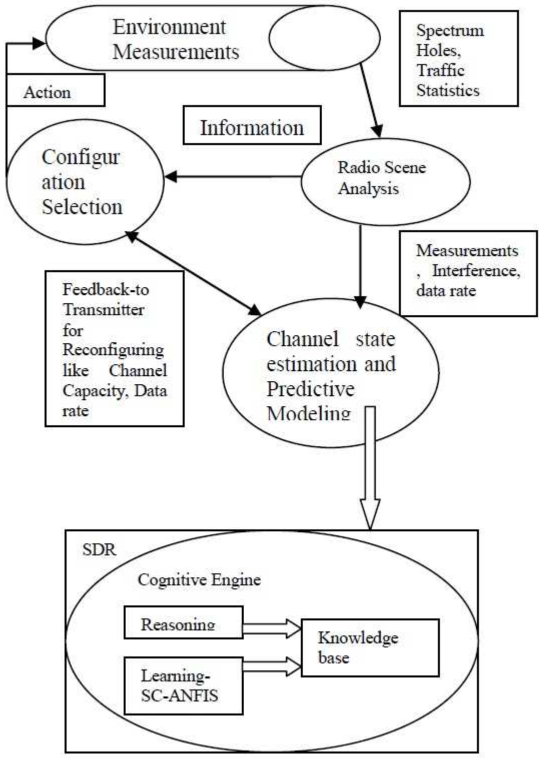


Fig. 1. Cognitive cycle and Engine

reliability, and efficiency. Reconfigurability capability is provided to CR by a platform known as software-defined radio [1], [2], [5], upon which a cognitive radio is built. SDR is a convergence of technologies of digital radio with computer software.The operation of CR is explained by considering the three tightly interconnected closed loop phases called cognitive cycle. Figure.1 depicts the simple three phases of Cognition cycle and Cognitive Engine [1], [2], [5].

**Radio-scene analysis** [1]–[5]: during this phase different radio configurations are probed to estimate the traffic statistics of radio environment so as to detect of spectrum holes. The traffic statistics is a measure of the sensed power in a certain frequency band and channel capacity. 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.

**Channel estimation and predictive modeling:** during which the capabilities of configurations are discovered (discovery process) and accordingly assessed, based on the measurements of the previous phase; moreover, past experience and knowledge can be exploited in this phase [1], [5]. **Configuration selection:** during which the transmitter sends the desired signal by means of the best. radio configuration (RAT, frequency, modulation, transmit power, data rate etc.), as it derives from the information of the previous two phases. The approach that is adopted here is that a cognitive radio results from the enhancement of a software radio with cognitive capabilities. Following above operations are embedded in engine called *cognitive engine* [5]. It includes learning, reasoning and knowledge base. So paper concentrates on learning base in the channel estimation and predictive modeling phase, for improving the stability and reliability of the discovery and evaluation of the configuration capabilities as it is depicted in Figure.1. In Our previous work [6], we have shown how ANFIS can be used as learning technique to predict data rate. This paper presents SC-ANFIS learning technique to predict the data rate. So that SC-ANFIS based learning schemes 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.

## III. SUBTRACTIVE CLUSTERING BASED ANFIS

ANFIS stands for Adaptive Neural Fuzzy Inference System. It was introduced by Jang in 1993 [7], [8]. It combines best futures of neural network and Fuzzy system. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way humans process information. ANFIS have many applications in many areas, such as function approximation, intelligent control and time series prediction [7]–[9].Fuzzy Inference system is Fuzzy model used to generate fuzzy If-then rules based on Input and output pair. And neural networks methods are used to train non linear membership functions parameters and linear parameters of rules.In our previous work [6], we have given detailed description of ANFIS architecture. Present work gives the explanations about subtractive clustering for ANFIS.

### A. *Principles of Subtractive Clustering For Rules Selection.*

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 (MFs) 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. Generally, it becomes very difficult to describe the rules manually in order to reach the precision needed with the minimized number of Membership Functions(MF), when the number of rules are larger than 3. Therefore, an automatic model identification method becomes a must, which is often realized by means of a training set of input-output pairs, $\{\mathrm{x}_i y_i\}, i = l...n$ $1001[7], [8], [10], [11]$.

The subtractive clustering algorithm is an attractive approach to the synthesis of ANFIS networks, which estimates the cluster number and its cluster location automatically. In subtractive clustering algorithm, each sample point is seen as a potential cluster center. By using this method computation time becomes linearly proportional to data size, but independent of the dimension problem under consideration [6], [8], [10]. Considering that the samples used in defining a model is a set of n data points $\{x_1, x_2 ... x_n\}$ in an M-dimension space. Assuming all data points are normalized to map within hypercube space, as every data is a candidate for determining cluster center. As a result, the density index $D_i$ corresponding to data $x_i$ is defined by

$$\mathsf{D_k} = \sum_{i=1} exp\{-\frac{\| x_i - {x_j}^2 \|}{(\gamma_a/2)^2}\} \tag{1}$$

In (1),$\gamma_a$ radius is a positive constant. Obviously, if specific data point $x_i$ has many neighboring data points then, it has high density value.The radius$\gamma_a$ gives the adjacent domain of $x_i$. Thus,those data beyond $\gamma_a$ have slight contribution to $D_i$. After density measure of each data point has been calculated,the data point with the highest density measure is then selected as the first cluster center and denoted as $x_{c1}$, and corresponding density is denoted as index $D_{c1}$.Then , the density of every data is recalculated as equation (2).

$$\mathsf{D_i}' = \mathsf{D_i} - \{\mathsf{D_{c1}} * exp\{-\frac{\| x_i - {x_j}^2 \|}{(\gamma_a/2)^2}\}\} \tag{2}$$

In(2),$\gamma_b$ is positive constant,which generally given as $\gamma_b$=1.5$\gamma_a$ [8], [11]. By(2),the data points near the first cluster center $x_{c1}$ will have significantly reduced $D_i$, which makes points unlikely to be selected as the next cluster center. Here $\gamma_b$ defines a neighborhood that has measurable reductions in density measure.After the density measure of each data point is recalculated, next cluster center $x_{c2}$ is selected and all of the density measures for data points are revised again.This process will be terminated until the density index of all reminder data is less than the given threshold. By using the subtractive cluster algorithm, the cluster center of all data is found out [8], [10], [11]. Then the number of subtractive centers are used to generate automatic membership functions and rule base, as well as the location of membership function within dimensions.

## IV. SC-ANFIS BASED EXTENDED DATA RATE PREDICTION

### A. Preparation Procedure

We assume that the ANFIS based scheme is tuned to arbitrary radio configuration e.g. WLAN 802.11a/g and its capabilities need to be discovered. The SC-ANFIS based scheme is to predict data rate that is obtained by the configuration being under investigation. We follow the algorithm presented in [5], to prepare input and target value. In our previous work [6] data rate prediction was considered for whole day. To increase complexity time zone factor is introduced. Day is divided into four time zones and during each of them the configuration in question is associated with mean, most usually observed data rate value, which is denoted as $\bar{m}_{tz} \in M$. Mean value enhances the learning scheme with feature of past experience. Detailed procedure to prepare data rate time series considering time zone parameter and target value $r_k^{trgt}$ found in [5].

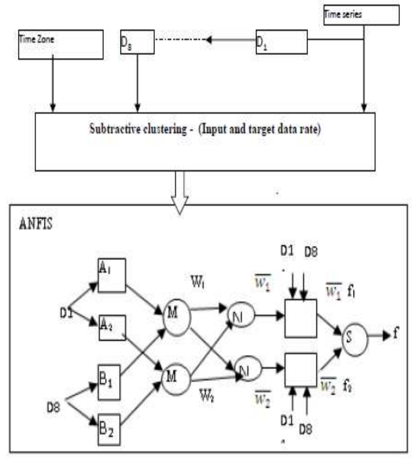


Fig. 2. SC-ANFIS model for prediction

Time window of 8 slots are considered. Here smoothing factor for time window $\chi = .7$ accordingly weights $\beta_i$ [5] change. Here it is assumed that the day is divided in four equal time zones as follows :06:00_12:00, 12:00 _18:00, 18:00_24:00 and 00:00_06:00. In each of these time zones a different mean value $\bar{m}_{tz}$ is observed, let them be set equal to 24, 6, 36 and 48 Mbps for each of the four time zones, respectively; this might reveal for instance the existence of high load situation during the mid working day. Since dimension of the problem is increased to 8, so conventional ANFIS is not used to predict the data rate, because it generates huge rules which cannot be handled by the simulation environment. Only faster method based on subtractive clustering is used to generate FIS. SC-based ANFIS has ability remove redundant rules and give best fit rules which determine the prediction. ANIFS model for training is shown in Figure.2.

## V. RESULTS AND DISCUSSION

RMSE, Prediction accuracy are used as performance index. Four time zone predictions are done with SC-ANFIS. For each zone 1000 training data points are taken and 100 data points are used for testing and validation. In testing case, simulation is carried out for 500 epochs.Trial and error method indicate t is found that Subtractive clustering method with radius of influence 0.8 gives best result.By Subtractive clustering automatically, required number of Gaussian membership functions (MF) are generated more detail is found in [8], [10], [11]. For four time zone results are tabulated in Table.1. Figure.3 to Figure.7 present detailed plot of MFs before training and after training, error curves and prediction accuracy respectively. Various neural network methods results are presented in Table.1, which are used in [2]. It can be seen that prediction accuracy very high as compared to neural network. If the rules criteria are allowed to have maximum, than ANFIS has infinite prediction ability as mentioned in reference [8], [10], [11].Number rules used for trained ANFIS are 6. And prediction accuracy for all four time zones is above 90 percentages.

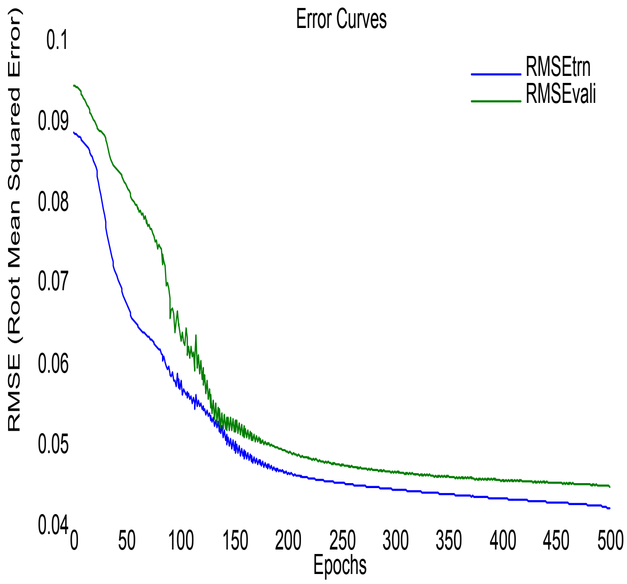


Fig. 3. RMSE curves after Training and Validation

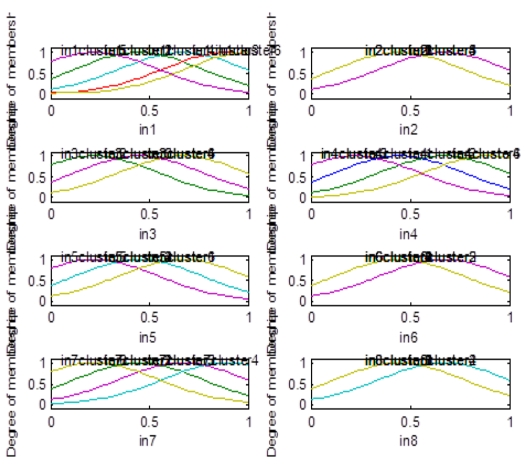


Fig. 4. Membership functions before Training FIS

Best case is third case, in which RMSE error difference is 0.0120 and prediction accuracy in case training and validation are 94 and 93 percentage. And this method provides faster training than NNs methods. Since number of tunable parameters compared to neural network are less, so it would make easy to be implemented in Hardware. From Table.1 it is seen feed forward (FF) neural network with 2 layers gave PA of 92 and 88 percentage in testing and validation and RMSE error difference of 0.0820.But number of tunable parameters are 218. Similarly if the number of hidden layers is increased complexity increases and learning process becomes slow and network also learns irrelevant details. Elman recurrent network and focused time delay

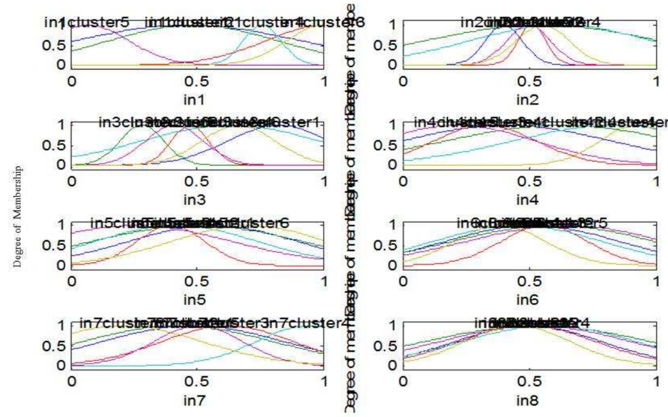


Fig. 5. Membership functions after training FIS

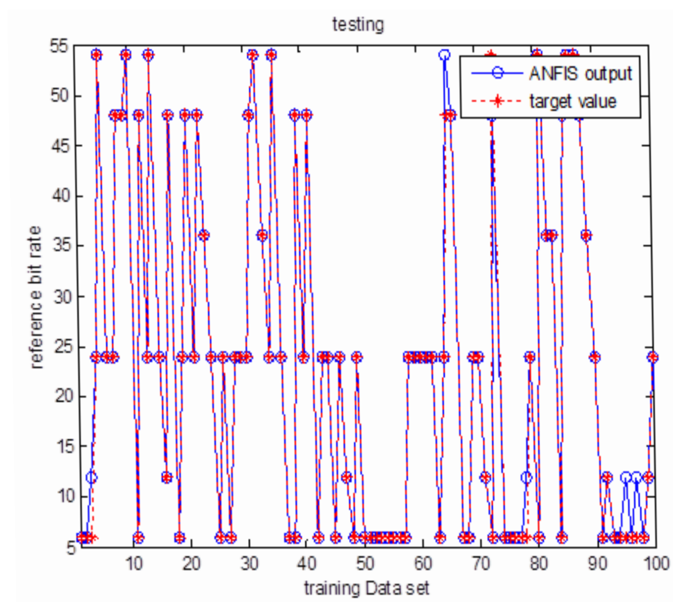


Fig. 6. Prediction Accuracy of SC-ANFIS in Training

network (FTDNN) which are considered good for time series prediction also doesnt perform well ,as compared to SCANFIS. Similarly if more complexity is increased by considering frame rate, environmental conditions .etc above neural network methods are not suitable. So ANFIS based method will be more suitable in learning process of cognitive radio. ANFIS method can be used to imbibe intelligence in prediction and modeling phase of cognition cycle.

## VI. CONCLUSION

Paper presents the ANFIS based data rate prediction for CR in learning with extended parameter as time zone. Paper

TABLE I
PERFORMANCE INDEX OF SC- ANFIS AND NNs TECHNIQUES

| Technique | Hidden node | Hidden Layer | Rules | $RMSE_{trn}$ | $RMSE_{val}$ | $RMSE_{trn}-RMSE_{vld}$ | Total Tunable parameters | Prediction in Training | Prediction in Validation |
|---|---|---|---|---|---|---|---|---|---|
| ANFIS-SC | - | 5 | 12 | 0.0236 | 0.1230 | 0.0994 | 158 | 94 | 89 |
| ANFIS-SC | - | 5 | 6 | 0.0328 | 0.1180 | 0.0852 | 150 | 97 | 91 |
| ANFIS-SC | - | 5 | 6 | 0.0573 | 0.0693 | 0.0120 | 175 | 94 | 93 |
| ANFIS-SC | - | 5 | 32 | 0.0118 | 0.2007 | 0.1889 | 850 | 100 | 88 |
| FF | 15 | 1 | - | 0.1115 | 0.1646 | 0.0531 | 158 | 84 | 77 |
| ELMN NN | 15 | 1 | - | 0.1225 | 0.1011 | 0.0124 | 383 | 76 | 73 |
| FTDNN | 10 | 1 | - | 0.0637 | 0.5947 | 0.5310 | 158 | 85 | 78 |
| FF | 10-10 | 2 | - | 0.903 | 0.1516 | 0.0613 | 218 | 92 | 88 |
| FF | 8-10-10 | 3 | - | 0.0642 | 0.1462 | 0.0820 | 300 | 83 | 82 |

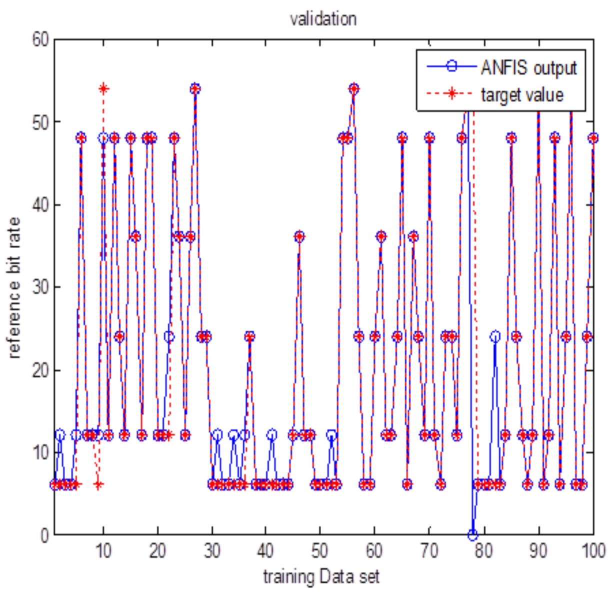


Fig. 7. Prediction Accuracy of SC-ANFIS in Validation

explores various types of previously used NNs methods. Here indirectly capability of radio configuration is estimated. CR needs learning techniques to act as intelligent radio. So our paper bring in SC-ANFIS as learning technique in channel estimation stage of cognitive radio to predict the Data rate of particular radio configuration. By predicting data rate of particular radio configuration proposed ANFIS based 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. This technique provides superior performance compared to previous neural network method in terms of RMSE error and prediction accuracy. 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. 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 formulised to include other parameters which affect data rate. The prediction was based on assumed scenario but to validate and check the robustness of ANFIS more realistic time series must be considered for training.

## REFERENCES

[1] H. Simon, “Cognitive radio: brain-empowered wireless communications,” *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 2, pp. 201 – 20, 2005/02/.

[2] I. Mitola, J. and J. Maguire, G.Q., “Cognitive radio: making software radios more personal,” *IEEE Personal Communications*, vol. 6, no. 4, pp. 13 – 18, 1999/08/.

[3] H. Arslan(Ed.), Ed., *Cognitive Radio, Software Defined Radio, and Adaptive wireless Systems*. Springer, 2007.

[4] M. Vuran, I. Akyildiz, W.-Y. Lee, and S. Mohanty, “Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey,” *Computer Networks*, vol. 50, no. 13, pp. 2127 – 59, 15 Sept. 2006.

[5] K. Tsagkaris, A. Katidiotis, and P. Demestichas, “Neural network-based learning schemes for cognitive radio systems,” *Computer Communications*, vol. 31, no. 14, pp. 3394 – 3404, 2008.

[6] P. Stavroulakis, *Neuro-Fuzzy and Fuzzy-Neural Applications in Telecommunications*. Springer, 2004.

[7] J.-S. Jang, “Anfis: adaptive-network-based fuzzy inference system,” *IEEE Transactions on Systems, Man and Cybernetics*, vol. 23, no. 3, pp. 665 – 85, 1993/05/.

[8] E. J.-S.R. Jang, C.-T.Sun, *Neuro-Fuzzy And Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Pearson Education, 2004.

[9] S. Hiremath and S. K. Patra, “Transmission rate prediction for cognitive radio using adaptive neural fuzzy inference system,” Mangalore, Karnataka, India, 2010, pp. 92 – 97. [Online]. Available: http://dx.doi.org/10.1109/ICIINFS.2010.5578727

[10] S. Chopra, R. Mitra, and V. Kumar, “Reduction of fuzzy rules and membership functions and its application to fuzzy pi and pd type controllers,” *International Journal of Control, Automation and Systems*, vol. 4, no. 4, pp. 438 – 447, 2006.

[11] P. Ming-bao and Z. Xin-ping, “Traffic flow prediction of chaos time series by using subtractive clustering for fuzzy neural network modeling,” vol. vol.1, Piscataway, NJ, USA, 2008//, pp. 23 – 7.