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Soft Computing based Learning for Cognitive Radio

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***Abstract*— Over the last decade the world of wireless communications has been undergoing some crucial changes, which have brought it at the forefront of international research and development interest, eventually resulting in the advent of a multitude of innovative technologies and associated products such as WiFi, WiMax, 802.20, 802.22, wireless mesh networks and Software Defined Radio. Such a highly varying radio environment calls for intelligent management, allocation and usage of a scarce resource, namely the radio spectrum. One of the most prominent emerging technologies that promise to handle such situations is Cognitive Radio. Cognitive Radio systems are based on Software Defined Radio technology and utilize intelligent software packages that enrich their transceivers with the highly attractive properties of self-awareness, adaptability and capability to learn. The Cognitive Engine, the intelligent system behind the Cognitive Radio, combines sensing, learning, and optimization algorithms to control and adapt the radio system from the physical layer and up the communication stack. The integration of a learning engine can be very important for improving the stability and reliability of the discovery and evaluation of the configuration capabilities. To this effect, many different learning techniques are available and can be used by a Cognitive Radio ranging from pure lookup tables to arbitrary combinations of soft Computing techniques, which include among others: Artificial Neural Networks, evolutionary/Genetic Algorithms, reinforcement learning, fuzzy systems, Hidden Markov Models, etc. The proposed work contributes in this direction, aiming to develop a learning scheme and work towards solving problems related to learning phase of Cognitive Radio systems. Interesting scenarios are to be mobilized for the performance assessment work, conducted in order to design and use an appropriate structure, while indicative results need to be presented and discussed in order to showcase the benefits of incorporating such learning schemes into Cognitive Radio systems. Subsequently feasibility of such learning schemes could be tested with simulations. In the near future, such learning schemes are expected to assist a Cognitive Radio system to compare among the whole of available, candidate radio configurations and finally select the best one to operate in.**

***Index Terms*— Cognitive Radio, Soft Computing techniques, Learning, Elman networks**

I. INTRODUCTION

The approach that is adopted herewith is that a cognitive radio results from the enhancement of a software radio with cognitive capabilities. Those capabilities are often provided by an intelligent instantiation of a software package, called a cognitive engine, which enforces decisions to the software-based radio by continuously adjusting its parameters, observing and measuring the outcomes and taking actions to move the

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radio into some desired operational state. Cognitive Radios are capable of learning lessons and storing them into a knowledge base, from where they may be retrieved, when needed, to guide future decisions and actions. A reasoning engine determines which actions are executable in a given radio environment

Different learning models are built toward spectrum behavior, spectrum sensing and Spectrum learning using approaches such as Collaborative filtering [1], self learning algorithms [2], and machine learning techniques [3]. Learning Models are also built towards Dynamic Channel Selection and Dynamic Spectrum Access using approaches such as Markov Model[4], Neural Networks[5], and Game Theory[6].

The learning engine is the intelligence behind the cognitive radio where the context awareness and the capacity to learn is implemented through methods like Support Vector Machine[7], Neural Networks[8], Genetic Algorithms[9], Reinforcement learning[10]. The decision maker of Cognitive Radio is built through a neural network based model [11]. Signal classification to detect the presence of unknown signal is implemented using self organizing maps [12].

Learning Models are also built towards finding parameters to decide which the best configuration to operate with is [13]. Transmission rate prediction is done through a learning model built using Neural Fuzzy Interference System [14]. Some learning models use supervised algorithms while certain use unsupervised algorithms such as self organized maps [15].Table 1 presents a comparative study of different existing methods illustrating their merits and remarks about the technique used. This provides a roadmap for the proposed methodology.

TABLE I. COMPARATIVE STUDY OF EXISTING METHODS

Method Adopted	Procedure	Advantages	Remarks
Q-Learning/Reinforcement Learning [10]	Secondary system modelling To implement cognitive cycle	Ability to converge Better network wide performance	Can be extended towards realising intelligence of the cognitive engine
Neural Networks [3],[5],[7],[8]	Intelligence Learning Engine Learning in Dynamic Channel Selection	Need less prior knowledge Can be used in any phase of cognition	Application of the model to different protocols and scenarios need to be analyzed
Fuzzy Logic [14]	Learning in Transmission rate Prediction	Reduced complexity More Accurate	Other parameters could be included to predict best radio configuration
Genetic Algorithms [9]	Learning & Optimisation	Multi-objective performance,non-mathematical, non-closed form constraints	Could be extended for incorporation of learning machine to automatically update weights
Game Theory [6]	Learning in Channel Selection	efficient use of the spectrum resources can derive higher utilities	Can be applied in next-generation products and services with enhanced capabilities
Markov Models [4]	Learning in Dynamic Spectrum Access	Training done in real time Improved throughput	Can also find a role in decision engine of Cognitive Radio

The future direction in the work is, learning complexity of these approaches should be investigated from both theoretical research and empirical study point of view to bring this technique much closer to reality. Large-scale simulations and experiments within a Cognitive Radio network would also be very interesting to see how this approach will perform under a relatively large communication network. Also, Future research directions include the extension of the these approaches to optimization problems with large solution spaces, as well as investigation of cooperative techniques for scheme, that are geared towards unsupervised learning such as Self-Organizing Maps.

Though different types of learning models have been developed for different aspects in cognitive radios, little work has been done on learning models trying to anticipate or discover performance of cognitive radio for varying radio configurations. The learning models fully exploiting potential of learning algorithms is yet to be built. Though models exist using supervised algorithms, models based on unsupervised algorithms still remain unexplored terrains. This brings in need for more research and is the main motivation. Such models are expected to assist CRS to choose among the different candidate configurations by taking into account the predictions of the performance that can be achieved.

Many different learning techniques are available and can be used by a cognitive radio ranging from pure lookup tables to arbitrary combinations of Artificial Intelligence (AI) and Machine Learning techniques and include among others: artificial neural networks, evolutionary/genetic algorithms, reinforcement learning, fuzzy systems, hidden Markov models, etc.

This paper contributes in this direction, to build a learning scheme using soft computing, towards discovering the system performance of various specific radio configurations in a Cognitive Radio system. The learning scheme relies on artificial neural networks supervised and unsupervised 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 following steps give the methodology to be used for the proposed work:

Step1: Deciding the requirements of database.

Step2: Selection of suitable platform for database collection.

Step3: Setup for database collection.

Step4: Database filtering.

Step5: Designing neural network based on

- i. Input output parameters.
- ii. Network type.
- iii. Network parameters
- iv. Database length

Step6: Analyze the results.

Step7: Redesign the network.

Initially the database is generated which forms the input for the neural network model. The data used for the test cases have been obtained from real measurements that took place in a real working environment within our college premises. Specifically, a laptop equipped with an Intel PROset/Wireless card has been used for measuring, among others, the maximum achievable transmission data rate, the signal strength in user predefined time intervals (with the default value being 3 sec). The laptop has been setup with a Windows OS and using the ipw3945 driver for the wireless card. Another laptop has been setup with same vision of windows OS but uses Dell Wireless 1702 wireless card. The wireless access point (AP) used was a D-Link broadband router (model WRT54GS) able to operate in both IEEE 802.11 b/g standard modes .This comprises the radio configuration (it can be seen as one single configuration given that the operating carrier frequency is the same, i.e. 2.4 GHz in both modes), the capabilities of which need to be discovered.

The following was the setup made for the database collection in Ad-hoc mode.The laptop has been setup with a Windows OS, equipped with an Intel PROset/Wireless card and using the ipw3945 driver for the wireless card.Another laptop has been setup with same vision of windows OS but uses Dell Wireless 1702 wireless card. The data collection lasted for 7 days over different time slots and the application used during that period included peer-to-peer (P2P) file sharing, web browsing and ftp. The database collected from the setup was in raw form, which can’t be used directly. The database file obtained from Intel PROset/Wireless card was html format which was translated into ms excel format. Subsequently, the data was filtered using matlab programming.

In order to derive and evaluate the performance of the most appropriate NN structure that better fulfils our objective, several scenarios and test cases comprising both commercial off-the-shelf and also simulated hardware and software have been set up and studied. In all scenarios, multiple, different types of NNs with a considerable number of adjustable parameters have been investigated through trial and error.

At first, it is commonly acceptable that the power of NNs is based on the training they received and consequently, on the availability of the set of exemplars i.e. on whether there exist enough data for training purposes. However, the conduct of our experiments was facilitated by the nature and availability of the needed measurements to act as input training set for the examined NNs It must be noted that there is a speed versus performance tradeoff while searching for the best NN structure. In all the scenarios that follow, training and validation were both curried out offline. This relaxes the strict requirements of the online case for fast training and convergence and as a result, no special focus was placed on the optimization of parameters that highly affect the NN's speed, such as the training set size or the number of training epochs, etc.

III. Proposed Methodology

Intel Wireless Card supports the IEEE 802.11a/b/g/n,802.11. It comes with Intel PROset/Wireless tool software. We can manage wireless connection and setup new connection. There is provision for monitoring advanced statistics like RSSI, No of packets transmitted and received at different data rates, transmitted bytes, received bytes, transmission retries, reception errors etc.

The statistics can be logged in form of html file.The snapshot of the Intel PROset software is shown in Fig 1. Intel PROset/Wireless card has been used for measuring, among others, the maximum achievable transmission data rate, the signal strength in user predefined time intervals (with the default value being 3 sec).

Depending on the test scenario the input output parameters for the system is decided. In this paper we consider three scenarios detailed below.

Scenario 1

For the first set of test cases of scenario 1, the focus was on the maximum achievable transmission data rate from a set of reference values that uniquely characterize each of the operating standard modes, e.g. according to IEEE 802.11g specifications the achievable raw data rates are in the set R1={1, 2, 6, 9, 12, 18, 24, 36, 48, 54} in Mbps. Those values are mixed with the ones from the respective IEEE 802.11b specifications, i.e. in the set R2= {1, 2, 5.5, 11} in Mbps. The target was to build a NN that would be able to predict those rates in the next single step, based on past measurements.

Scenario 2

For the test cases of the second scenario, the focus is again on the achievable transmission data rate. Though, the target in this scenario is to build a NN that would be able to predict the achievable bit rate, taken as input the quality of the link and the signal strength of the wireless transceiver. For this purpose, measurements collected by the wireless card have been used, as in the previous case. According to the used driver (ipw 3945) specifications, the link quality takes integer values in the range of [1, 100], while the signal strength is measured in dBm.

Scenario 3

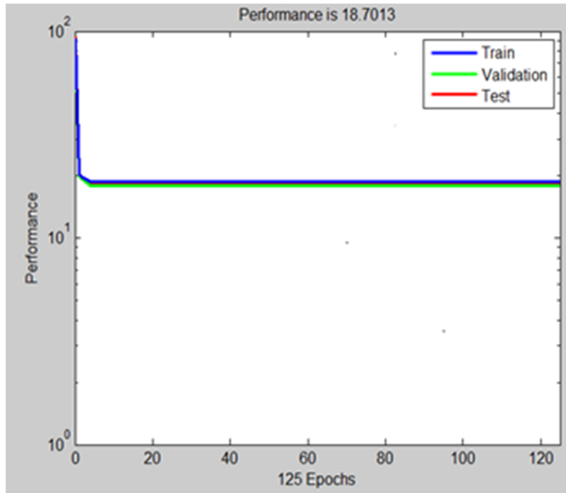
The target on the previous scenarios was to build a NN that would be (a) to characterize the environment based on measurements that have been recorded for a long period of time and (b) to make predictions. For that, the measurements lasted for one week, as already mentioned and a large number of data have been used to train the networks to predict following communication performance. In a real life example, such networks could be used in situations for which the user communicates in a specific environment, with more or less stable conditions, where the training could last longer and capture all the changes in the conditions of the environment. In such a case, the NN would be able to perform well, giving predictions close to the expected values, as seen in the previous cases.

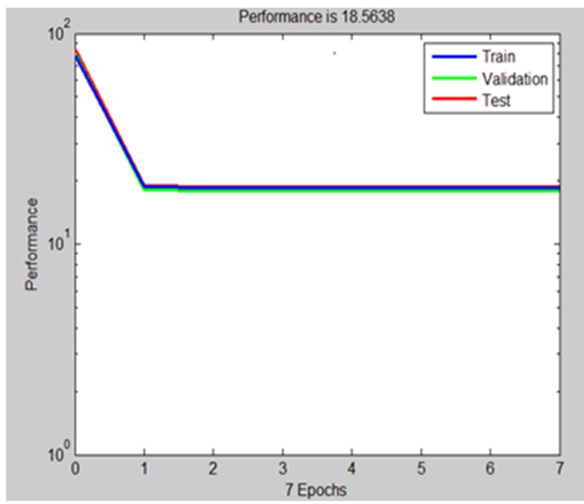
The neural network model used is Elman Network. The Elman network commonly is a two-layer network with feedback from the first-layer output to the first-layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns.

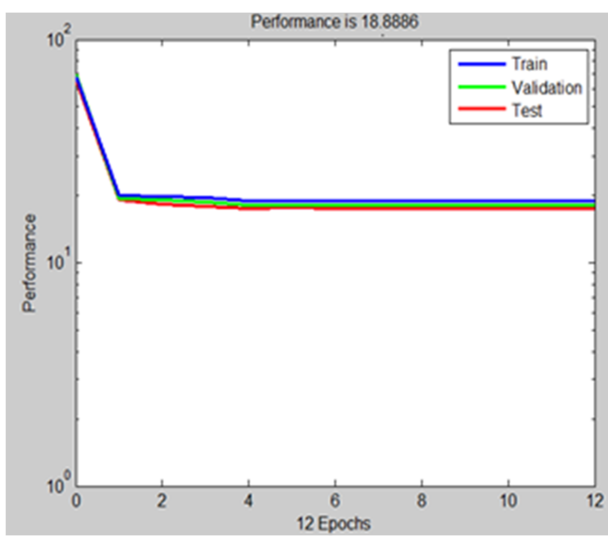
The Elman network has tansig neurons in its hidden (recurrent) layer, and purelin neurons in its output layer. This combination is special in that two-layer networks with these transfer functions can approximate any function (with a finite number of discontinuities) with arbitrary accuracy. The only requirement is that the hidden layer must have enough neurons. More hidden neurons are needed as the function being fitted increases in complexity.

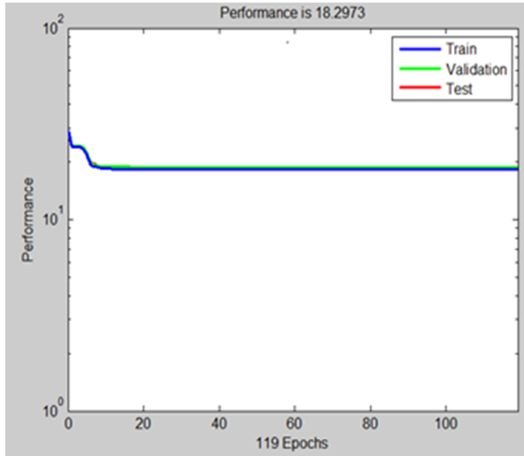
The Elman network differs from conventional two-layer networks in that the first layer has a recurrent connection. The delay in this connection stores values from the previous time step, which can be used in the current time step. Thus, even if two Elman networks, with the same weights and biases, are given identical inputs at a given time step, their outputs can be different because of different feedback states. Because the network can store information for future reference, it is able to learn temporal patterns as well as spatial patterns. The Elman network can be trained to respond to, and to generate, both kinds of patterns.

The following Figures 1 show the simulation results for scenario 1


Performance is 18.7013
Train
Validation
Test
Performance
10^2
10^1
10^0
0
20
40
60
80
100
120
125 Epochs
1)


Performance is 18.5638
Train
Validation
Test
Performance
10^2
10^1
10^0
0
1
2
3
4
5
6
7
7 Epochs
2)

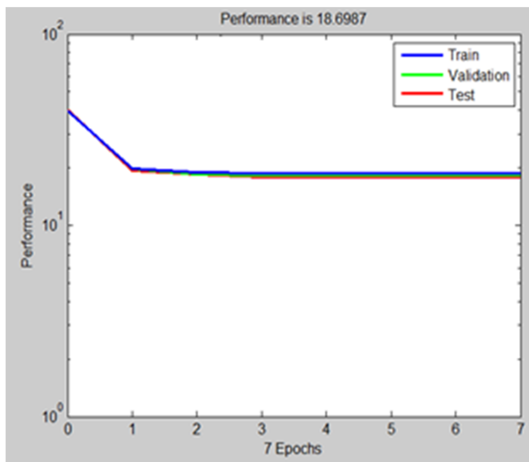

Performance is 18.8886
Train
Validation
Test
Performance
10^2
10^1
10^0
0
2
4
6
8
10
12
12 Epochs
3)



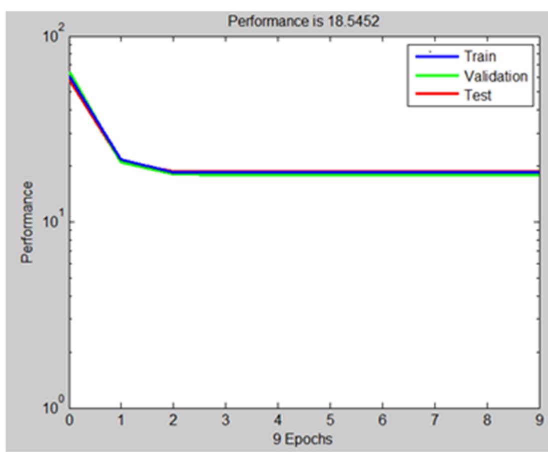
4)

Fig 1: Simulations for Scenario 1

The following graphs show the simulation results for scenario 2



1)



2)

Fig 2: Simulations for Scenario 2

It is seen that when fed with the known sequence, the NN actual output seems to follow the target values (that are expected according to the input that feeds the NN), giving a few errors, which shows that the network has been trained well. The same applies for the unknown sequences. The NN performs well during the validation session and it can be observed that the network has learned the basic structure of the data, whereas at the same time it has managed to generalize well.

The above leads to the conclusion that the NN has been trained well and performs also well under the specific environment (within the college premises). In other words, the NN has obtained knowledge regarding the behaviour of the environment and it is able to make predictions at a very good level. The scenario 1 reveals the potential of the NNs to handle time series data. The NN has learned to identify patterns and to predict the achievable transmission data rate, without knowing any other details (e.g. the signal strength (see scenario 2), etc.), except for the past observations. This last statement justifies why a delay line of 100 slots in FTDNN gives better results, compared to the other cases.

If the time series is increased beyond 100 slots the time for learning is too large as compared to the change in mse. Also the increases in no of hidden layer beyond 10 neurons per layers degrade the performance due to function over fitting. The no of epochs show significant improvement in error till value of 100, beyond which the there is hardly any improvement in error. Also the time required is significant making learning inefficient. Following case explains why a large value of epochs like 1000 is not suitable. It can be seen that there is no significant improvement beyond 100 epochs.

Scenario 2:

Figure 2 illustrates the simulation for Scenario 2 including training and testing. A number of different test cases have been investigated. Again, all networks use the tansig function for the neurons in their hidden (recurrent) layer(s) and the purelin function for the single neuron in their output layer. The bias and weight values are updated according to trainlm optimization, during training sessions.Finally, once again, the MSE has been used for measuring the performance of the neural networks.

The case of focused time-delay neural network gives better performance ant it seems logical, since smaller networks do not have the ability to distinguish between the different types of input (separate the problem). Conversely, adding more neurons into the two hidden layer network does not raise the performance of the network. Actually, the error increases when more hidden neurons are used. This is normal since there is a theoretically best performance that cannot be exceeded by adding more neurons; the network learns irrelevant details of the individual cases. In general, the proposed NN performs well. It is able to generalize well, giving output values very close to the target values.

The NN was able to predict at a very good level, which shows that it has learned how to associate the signal strength with the achievable transmission data rate, in the specific environment. Finally, the use of less hidden layers resulted in the improvement of the network performance, which could not be achieved by deploying a larger delay line as in scenario 1.

Scenario 3:

Many simulations were carried out with different network configurations, but the errors were quite large and consistent. It shows that more parameters needed to be considered to predict the required throughput, like time, location, user preferences or even weather conditions, etc. will play very important role in this scenario. The behavior of the user is also very important. Tests with the consideration of other important parameters needed to be done in future .

After a series of testing with different types of NNs (including Elman networks that have been defined in the scenario 1,linear networks and feed-forward networks), we had concluded that the Elman type of networks performs better in all circumstances.

IV. CONCLUSIONS

Through the work done in paper, anticipation of performance of one or two operating parameters in Cognitive Radio was done based on learning accomplished in the learning model for various learning configurations leading to intelligent Cognitive Radio. The built learning model will aid in analyzing the feasibility of implementing such learning models in larger scales towards improving efficiency of the cognitive radio in the highly varying radio environment. If possible these models could be further expanded to look into real life performances. Such approaches might not only bring new insights of machine learning research for cognitive radios, but it will also potentially provide new techniques to fully accomplish the cognitive capabilities of cognitive radios. Furthermore, new types and enhanced structures of NNs that have been found to improve both short-term and long-term time-series prediction capabilities will be investigated for application to our scheme, including also NNs that are geared towards unsupervised learning such as Self-Organising Maps.Last but not least, as long as evidence on the performance capabilities of each candidate radio configuration of the cognitive terminal can be drawn, the optimization process/algorithm for selecting the optimum one also needs to be thoroughly studied as part of our future.

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