Machine Learning Implementation in Cognitive Radio Networks with Game-Theory Technique

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Abstract: Significant enhancement of spectrum utilization can be performed by means of Cognitive Radio technology. A game theory based Cognitive Radio Network with Dynamic Spectrum Allocation model is proposed in this paper. M|M|1 queuing model is implemented along with Preemptive Resume Priority for accommodation of all the cases. An Incremental Weights-Decremental Ratios (IW-DR) algorithm based on priority-based scheduling is used for supplementing this theory. Regression models are used for restructuring and improving the efficiency of the system.

Keywords: Regression; Game Theory; Queuing Theory; Spectrum Allocation; Cognitive Networks;

1. Introduction

The developments in wireless spectrum and growing demands has an issue of a serious insufficiency in the unlicensed spectrum in this rapidly improving digital age [1]. The number of devices and applications dependant exclusively on the unlicensed bands availability is increasing exponentially. Under-utilization of licensed bands and congestion in unlicensed bands are the contrary scenarios in these devices and applications. The use of the channels effectively is performed by the wireless services prospective growth [2]. The limited radio spectrum and its deficiency issues can be alleviated by the novel solution of Cognitive Radio (CR) Networks. Depending on the spectrum environment, the configurations are adjusted for their competence with the devices that are intelligent and spectrum-agile in the CR Networks [3]. Primary and Secondary Users (PU & SU) are the two major types of CR networks that use the spectrum of obligatory licensed users and licensed spectrum that is unused with opportunistic access respectively. Dynamic Spectrum Access is the composite term used for this feature. Avoiding the Quality of Service loss and harmonious coexistence are ensured in the corresponding networks on a peaceful basis [4].

The dynamic spectrum allocation is proposed in leasing, auctions, game theory and other such applications. The contradictory interest of the players and their interactions are modelled and developed using robust tool in the game theory [5]. Rationality of every player in the game is a premise in implementing the game theory. The payoffs of the players can be maximized individually by the SU by the rational game players. The channel allotment and payoff is as follows [6]. The PUs are relinquished by the available channels for competing with the SU players in the dynamic non-cooperative game as proposed in this work. The SU collision is dodged in a fashion that the available networks stay or switch

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between each other in this strategy [7]. On acquiring the accessible channel in the SU on achieving the equilibrium point of the game. A dynamic spectrum access technique is set up in the game-theory environment. Formulation of Nash equilibrium is performed for the game [8]. The simulation of the game is performed and implemented using regression techniques. Based on the channel availability, the traffic surpasses system failure. This is a major setback of this system. This setback is amended by the work in this paper. The IW-DR Scheduling Algorithm and M|M|1 Queuing Networks with PRP is used for resolving this issue and relieving the congestion [9].

The performance of all SUs in spectrum allocation of Game theory cannot be guaranteed to be of the same levels. The Incremental Weights-Decremental Ratios (IW-DR) is the scheduling algorithm that is customized for this purpose in this work. According to the sensitivity order and type of application, QoS is achieved by the application of secondary user that is delay-sensitive for the bolster [10]. The continuous datasets are analyzed with several regression algorithms for implementation of learning in the game. For this purpose, Random Forest Regression, Decision Tree Regression, Support Vector Regression, Polynomial Regression and Simple Linear Regression is used for prediction of optimal probability. The channels available N_C and network count N_N for an optimal probability is obtained using the game environment that is simulated [11].

2. Architecture of the System

In X_r channels, the competing SUs or the total network count is represented by Y_r and at any particular time instance, the channel count available is represented by X_r in a dynamically changing game environment for the experimental scenario. Assume $(1/\lambda_T)$ be the arrival time and T_{EQ} is the channel accommodation time which is lesser than the arrival time. Two subcases namely switch and stay are categorized based on Y_r and X_r. Figure 1 represents the proposed system in which the channels are represented by squares. A 10 channel 8 network system is used for this purpose. In step 1, (SU5, SU6), (SU2, SU4) and (SU3, SU1, SU7) tuples have a collision. Similarly, in step 2, (SU4, SU6) and (SU2, SU1) as well as in step 3, (SU4, SU1) tuples have collision. Based on the optimal probability, the problem in each scenario is dealt differently.

A game is simulated using Game Algorithm replicating the game scenario. Further, the time taken for achieving equilibrium is calculated for every value of P that ranges between 0.99 and 0.01. 100 iterations of this process is performed for every tuple of (M, N and P) and the calculation of the mean equilibrium time is done. The least equilibrium time is selected for optimization of probability for the (M,N) tuple. This input attains an output of (M,N,P_0) tuple.
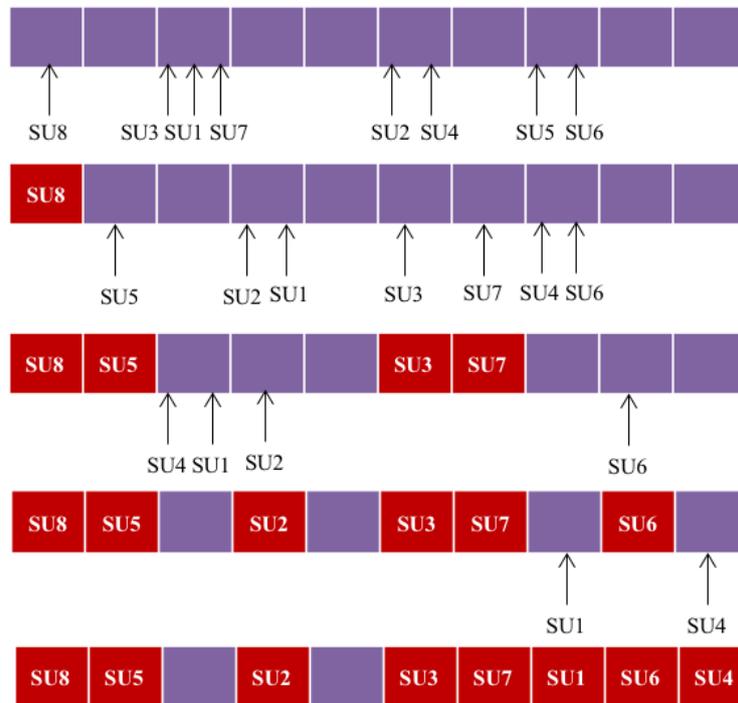
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Figure 1: 10 channel-8 network dynamic game illustration

3. Proposed Work

The system in which just one independent variable is available is termed as simple linear regression and the availability of multiple independent variables is termed as multiple linear regression [12]. The mathematical representation of this regression method is as follows:

$$f(x) = \omega_0 + \omega_1 x_1 + \omega_2 x_2 + \cdots + \omega_d x_d \quad \text{-----(1)}$$

$$f(x) = \omega_0 + \sum_{j=1}^{d} \omega_i k_i(x) \quad \text{-----(2)}$$

The input variables x=(x_1, x_2,…x_d) and linear parameter functions ω=(ω_0, ω_1,…. ω_d) are the reason behind the name linear regression. Any permanent offset in the information is allowed by a parameter ω_0.

In comparison to Linear Regression, a more versatile algorithm called Polynomial Regression is available which is quite similar in certain aspects [13]. Basis function is the major difference in these algorithms and is represented by the following expression:

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$$\varphi_i(x) = x^i \text{ -----(3)}$$

(M-1) is the degree of polynomial. Constant, first order and second order polynomials are chosen based on the value of M which can be 0, 1 or 2 respectively. The training dataset that fits our application best is chosen.

The classification principle used for SVM is also used in Support Vector Regression [14]. The hyperplane and data points are separated maximally by the multidimensional space where data is separated using the hyperplane. The limits are maintained within ε for deviation so as to have the allowed tolerance of errors and to calculate the value of f(x). The linear function can be calculated with the following expression:

$$f(x) = \omega x + \beta \text{ -----(4)}$$

The branches that represent the item observation is used for concluding regarding the leaves that represent the target value of the item that provides the predictive model of the decision tree using the decision tree regression [15]. Classification and Regression Trees (CART) is used for building the decision tree using the metric called Gini Index in which every class probability is represented by ρ_I and class by C. This is represented by the following expression:

$$Gini\ Index = 1 - \sum_{i=1}^{c}(\rho_i)^2 \text{ -------(5)}$$

The mean of individual trees are predicted and presented as output and the training time is used for construction of the decision trees in a large number for regression in ensemble learning technique using random decision forest. The decision tree regressions over fitting problem is solved using this method. The decision tree feature can be calculated using the following expression where the random forest model trees are calculated using the major feature RFfij:

$$Norm\ fi_m = \frac{fi_m}{\sum_{n\ call\ features} fi_n} \text{ -------(6)}$$

4. Results and Discussion

Scientific Python Development Environment (SPYDER) in Python is used along with Anaconda framework as an integrated development environment (IDE) which is open source for the purpose of simulation. Reasoning and learning capabilities are to be equipped in the cognitive radio networks to

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enable the system to operate efficiently. The need for self-learning is the inability of the channels to search and sense for other channels in the surroundings. An efficient dataset is used for coupling learning along with the games. The channels available N_C and network count N_N for an optimal probability is obtained using the game environment that is simulated.

Table 1: Probability comparison for various strategies

	EXP	RFR	DTR	SVR	PR	SLR
50	0.54	0.56	0.54	0.55	0.49	0.58
45	0.55	0.55	0.54	0.55	0.58	0.61
40	0.66	0.66	0.68	0.64	0.66	0.64
35	0.67	0.67	0.68	0.71	0.69	0.67
30	0.71	0.73	0.73	0.73	0.71	0.70
25	0.70	0.74	0.73	0.73	0.72	0.73
30	0.72	0.72	0.73	0.72	0.74	0.76
15	0.77	0.77	0.77	0.74	0.76	0.79
10	0.83	0.81	0.81	0.81	0.82	0.82

The predictive algorithms used here are Elastic Net Regression, Support Vector Regression and Linear Regression. Random Forest Regression, Decision Tree Regression, Support Vector Regression, Polynomial Regression and Simple Linear Regression are also implemented in this work as represented in Table 1. 99.8% enhancement is obtained by the results of Simple Vector Regression and 97.7% for Linear Regression. The available channel count is surpassed by the SUs traffic which did not support the case. The IW-DR Scheduling Algorithm and M|M|1 Queuing Networks with PRP is used for resolving this issue.
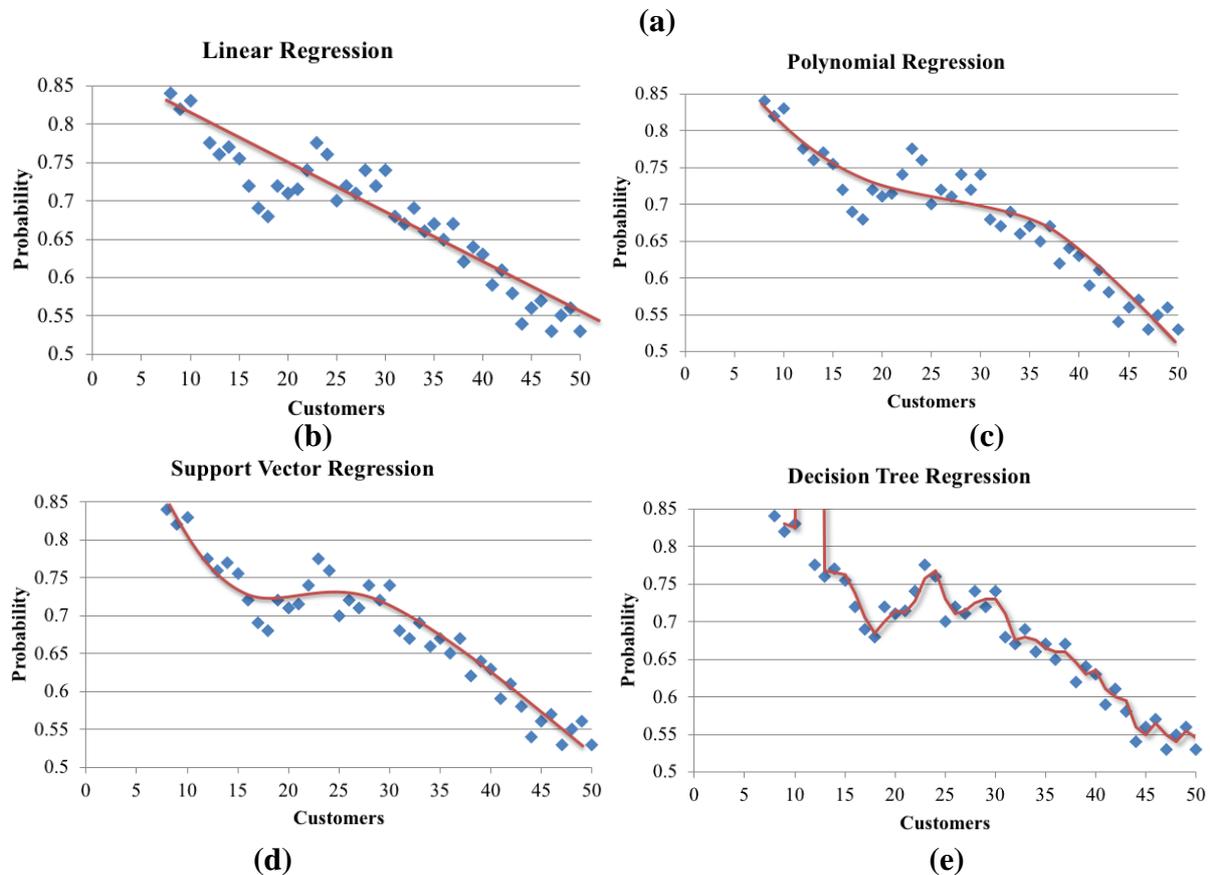
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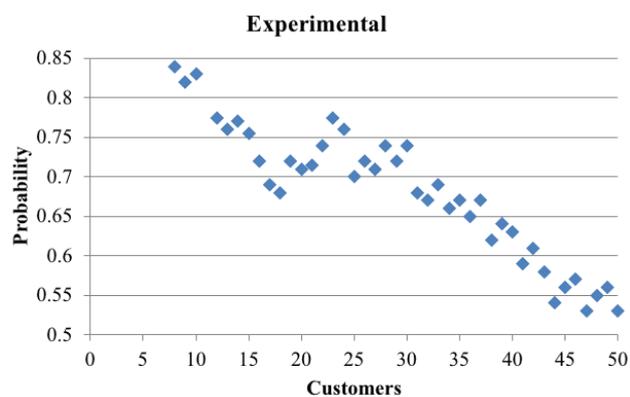
Figure 2: Comparison of Optimal Probability Vs Customers in (a)Experiment, (b) Linear Regression, (c) Polynomial Regression, (d)Support Vector Regression and (e) Decision Tree Regression

The total datasets simulated here is 820. They range between 10 to 50 for several possible combinations of game algorithms. Out of these datasets, for testing purpose, we use 164 datasets and for training purpose we use 656 datasets. A 3 column database is used for storing the database – namely Optimal Switching Probability (P_0), Number of Networks (N) and Number of Channels (M). Five regression algorithms namely Random Forest Regression, Decision Tree Regression, Support Vector Regression, Polynomial Regression and Simple Linear Regression are proposed in this work. The experimental results obtained by the Game algorithm for comparison of optimal probability and the customers is represented in Figure 2 (a). Comparison with the other compared algorithms is shown in Figure 2 (b), (c), (d) and (e). With the raise in the number of competitors, the switching probability drops according to the graph.

5. Conclusion

Dynamic Spectrum Allocation is improved by the implementation of the non-cooperative dynamic game. M|M|1 Queuing Network with PRP is used for steering the secondary user traffic in this paper.

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The users of various classes in the queues are provided equality using the IW-DR Scheduling Algorithm. Five regression algorithms namely Random Forest Regression, Decision Tree Regression, Support Vector Regression, Polynomial Regression and Simple Linear Regression are compared and analyzed with the results of the proposed work for inducing the non-cooperative game with self-learning capability.

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Author's Biography

Dr. Jennifer S Raj received the Ph.D degree from Anna University and Master's Degree in communication System from SRM University, India. Currently she is working in the Department of ECE, Gnanamani College of Technology, Namakkal, India. She is a life member of ISTE, India. She has been serving as Organizing Chair and Program Chair of several International conferences, and in the Program Committees of several International conferences. She is book reviewer for Tata Mc Graw hill publication and publishes more than fifty research articles in the journals and IEEE conferences. Her interests are in wireless Health care informatics and body area sensor networks

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