Resource Allocation and Optimization in Cognitive Radio using Cascaded Machine Learning Algorithm

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Abstract

The scarcity of dynamic spectrum allocation is a major issue in wireless networks. The limitations and bottleneck problems of wireless network addressing with cognitive radio networks,the cognitive radio network-based framework changes the dynamic resource allocation and ensures the ability of resources for primary and secondary users. The process of resource allocation and optimization enhances the performance of the cognitive radio network. The major issues related to cognitive radio networks are power control and spectrum allocation. This paper proposes a cascaded machine learning algorithm for the allocation of resources and the utilisation of power in a cognitive radio network. The proposed cascading algorithm of resource optimization focuses on energy efficiency, fairness, and spectrum utilization. The cascading algorithm trained the factors of energy and spectrum approach for the allocation of secondary users. The proposed algorithm dynamically manages resources and predicts new optimal resources. The proposed algorithm increases the rate of convergence of resource allocation. The proposed algorithm is simulated in MATLAB tools and applies standard parameters for the validation of proposed algorithms. The proposed algorithm results are compared with existing algorithms. The performance of the results suggests that the proposed algorithm is efficient in terms of resource allocation and power control.

Keywords: - Cognitive Radio Network (CRN), Machine Learning, Energy Efficiency, Resource Allocation, Spectrum Utilization.

Introduction

The emergence of wireless communication requires the proper allocation of spectrum and efficiency of energy. The management of spectrum allocation in wireless communication deals with various factors such as fairness, throughput, and efficiency of energy. The cognitive radio network handles and manages resource allocation and utilisation of insufficient spectrum allocation in wireless communication. The growth of wireless communication and the integration of the internet of things need quality of service and high-speed data. In cognitive radio networks (CRN), they can be categorised as primary and secondary as per spectrum condition. The CRN system handles channel resource allocation in terms of primary and secondary users. When sending and receiving data from other users, the user makes use of the channel[1,2,3]. The signal strength while using a certain channel determines the dependability of the data packet sent by a node to another user. As a result, wireless technology interference problems are unavoidable. When two nodes use the same channel, interference develops. However, if the same node uses a channel placed next to it, interference will dramatically rise. Also, Dynamic Spectrum Access (DSA), which uses Cognitive Radio Users (CRU) to assign the channel, is another name for Cognitive Radio Networks (CRN), which are used to assign channels. On the other hand, a machine learning-based model that is crucial for using the channel's capacity has been proposed [10], in which big base stations are placed in strategic areas while smaller base stations are projected as followers. Additionally, some earlier research concentrated on allocating a sub-channel, and the authors [11] stated that it uses an equilibrium game theoretic technique to reduce the disruption brought on by big base stations. Additionally, the author in [12] utilised hybrid methods with the aid of a customised Stackelberg game-specific methodology. A technique of regulating the power of diverse systems has been proposed in [13] in conjunction with [11, 12]. CRN was also created with swarm intelligence-based algorithms such as ACO and PSO [4], with the aim of creating the Common Control Channel. The goal of the Common Control Channel is to administer and maintain the SU or PU channel. The Secondary User node and channel resources were mapped into a matrix in a related piece of work [5]. To test the fairness of channel use, their goal was to separate the three methods into different topologies. The Color Sensitive Graph Colouring (CSGC) method was contrasted with their ACO system. This paper proposes a cascaded machine learning algorithm for cognitive radio network channel allocation. The constraints of function utilise the defined learning rate for channel allocation and decrease the interference of channels. The cascaded algorithm works in two segments: channel allocation and power control. The rest of the paper is organised as in section II. Related work, in section III, proposes an algorithm for resource optimization; in section IV, describes the experimental results analysis; in section V, conclusion and future work.

II. Related Work

Many researchers focus on maximising the throughput of cognitive radio networks and assisted wireless networks. The role of resource optimization increases the efficiency and performance of wireless networks. The major challenges for the management of resources and control of power in terms of energy efficiency are identified. Machine learning and swarm-based intelligence algorithms play a vital role in spectrum allocation. recently proposed several algorithms for resource allocation, some of which are described here.In this [1] author develop a distributed artificial intelligence approach for intelligent resource allocation that uses efficient multiagent learning in a WSN situation. In terms of cooperative networking and efficient resource allocation, the cost function and energy usage show a significant improvement.In this [2] author proposed Allocating fog layer resources has been made possible and processed using the Markov model learning method, which quickly determines the required probability of each item to resources in order to reduce latency and maximize network usage. According to the findings, the proposed research is successful and promising.In this [3] author introduce the random edge graph neural network (REGNN), which conducts convolutions over random graphs created by fading interference patterns in wireless networks, as well as an unsupervised model-free primal-dual learning approach for training the REGNN's weights. they demonstrate the great performance REGNNs achieve in comparison to heuristic benchmarks, as well as their transferrable capabilities, using numerical simulations.In this [4] author propose the underlay cognitive radio network (CRN), a joint channel selection and power adaption system that maximizes the data rate of all secondary users (SUs) while ensuring the quality of service (QoS) of main users (PUs). The simulation outcomes show that the new system is feasible and convergent, and that its performance has greatly improved. In this [5] author propose resource allocation options for UDN in five G and beyond networks in order to identify the resource allocation problem in many UDN situations, a taxonomy based on approaches, methodologies, and optimization criteria was reviewed in the early phase. Finally, the researchers are kept up to date on emerging technologies, challenges, and active research projects that demand their attention.In this [6] author propose delay aware scenarios, a UAV-based cognitive radio network with energy harvesting (EH-UAV-CRN) is used. By varying the MMROP thresholds, simulation outcome show that their technique may be employed flexibly in a variety of delay-related scenarios. In this [7] author propose a fast FNSNMF algorithm is presented. The proposed method begins by demonstrating that the derived sub-cost problem's function is convex and the accompanying gradient is Lipschitz continuous. their method is substantially faster than NSNMF at achieving nonlinear convergence. Simulations using both computer-generated and real-world data show that their methodology outperforms the alternatives.In this [8] author presents an overview of machine learning-based routing and resource allocation in optical networks. they begin by discussing the routing and wavelength allocation (RWA) problem in WDM optical networks, the RSA problem in EONs, and the RCSA problem in SDM optical networks.In this [9] author propose a new framework for implementing the LTE-U standard that uses existing LTE-A infrastructure and cognitive radio (CR) technology to detect the radio environment and create a spectrum map that the LTE-U system can use to optimize overall system throughput by executing joint power and channel allocation.In this [10] author provide the definition of Het Nets and the many network scenarios that they can be used in. Second, the topic of RA models is discussed. The purpose of this study is to present key information about Het Nets that may be utilized to influence the creation of more efficient strategies in this field of research. In this [11] author propose clustered IoT networks, a new distributed block-based Q learning method for slot scheduling in smart devices and MTCD has been developed. show the efficacy of their proposed strategy, in which each MTCD is assigned an appropriate slot with acceptable SIR levels, and the IoT network efficiently converges to a collision-free transmission with minimal intra-cluster interference.In this [12] author investigate the resource allocation design for intelligent reflecting surface (IRS)-assisted full-duplex (FD) cognitive radio systems. The suggested approach not only achieves a significantly greater secondary system spectral efficiency than numerous baseline schemes, but it also confirms its robustness against CSI uncertainty.In this [13] author propose the CRSN in spectrum leasing mode is taken into account. Secondary Users (SUs) convey information to Primary Users (PUs) in the CRSN, and PUs lease some spectrum usage time to SUs as a payment. The efficiency of the joint optimization technique in improving system throughput is demonstrated by simulation outcomes.In this [14] author propose Multiple secondary users (SUs) acquire both the wireless energy and the approved spectrum from the primary user (PU) to interact with a secondary access point is proposed for a wireless powered cooperative cognitive radio network (SAP). The trade-off between SU fairness, PU throughput, and SU sum-throughput is revealed through simulation outcome. In this [15] author addresses a variety of resource allocation options based on QoS efficiency when executing commonly performed tasks. While increasing the number of application submissions, the proposed algorithms outperformed other current algorithms in terms of overall data processing time, cost of instance, and network delay.In this [16] author HCCRN is a hybrid optimization approach for CCRNs that improves resource allocation. This work initial contribution is to offer a load balance augmented particle swarm optimization algorithm for energy-efficient cluster creation that avoids queuing issues. Users obtain required resources via the proposed HCCRN, resulting in energy efficiency, fairness, throughput, and QoS, according to simulation outcomes.In this [17] author a hybrid optimization technique with an efficient decision-making mechanism. Furthermore, the simulation outcome show that the best solution is found for each subordinate user in the entire network, taking into account capacity, spectrum sharing, data rate, and interference.In this [18] author proposed Net Soft-Sec-mission Loc's is to deliver guaranteed security and location services while also meeting their software resource needs. Net Soft-Sec-Loc is described in detail. they conduct a full simulation to show the benefits of the Net Soft-Sec-Loc framework. For comparison, they chose frameworks and resource allocation mechanisms that are most similar.In this [19] author propose SDN technology is used to optimize collaborative resource allocation of MEC and reduce edge server delay in the transmission process using two optimal edge server deployment techniques, EOESPA and RNOESPA.The outcome shows that, in various scenarios, when the number of deployment increases from one to four. In this [20] author proposes new use-cases that demonstrate how CRAN technology can increase their performance include heterogeneous CRAN, millimetre-wave CRAN, virtualized CRAN, NOMA-based CRAN, and full-duplex enabled CRAN. A thorough taxonomy of optimization methods and solution approaches with varied objectives is also supplied and discussed.

III. Proposed Methodology

The proposed algorithm of allocation of resource optimization of cognitive radio network describes in two sections. In first section describes the system model of cognitive radio network and formulation of problem, in second section describes the cascaded machine learning algorithm for resource allocation and optimization of energy factors in cognitive radio networks.

Section one

System Model

This paper considers OFDMA (orthogonal frequency division multiple access) cellular cognitive network as shown in figure1. The design network model has one primary base station (PBS) and one cognitive base station (CBS). The processing of users as the PBS associated with primary user and CBS associated with secondary users. The PBS and CBS uses same resource of spectrum. The PU's licensed frequency band resources may be used by the SU as long as it adheres to the underlay access model and stays within the PU's interference acceptability range. Figure 1 shows the communication between SU and CBS as the blue line and the communication between PU and PBS as the black line. The interference from the CBS to the PU is shown by the red line and needs to be regulated within a specified range.

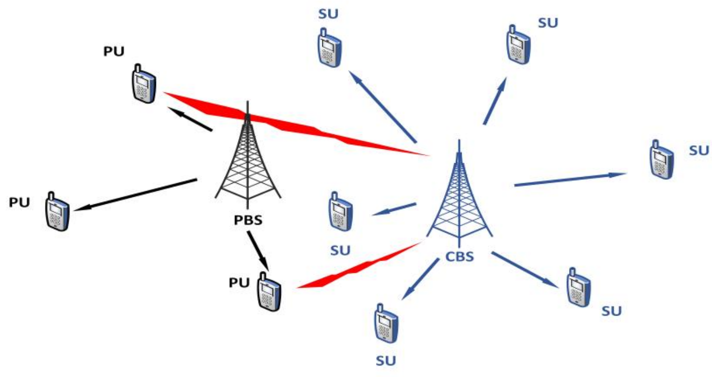

Figure 1 System model of cognitive radio network

The formulation of system as

$$P = min \sum_{c=1}^{c0} M^c \sum_{j=1}^{N} A_i \, B_{ij\ c}, Djc, Ejc \dots \dots \dots \dots (1)$$

Such that

$$Djc \le D_C^*, \ \ \forall c, j \dots \dots \dots \dots \dots \dots (2)$$

$$Fj, c \ge F_j^*, \forall C, j \dots \dots \dots \dots \dots (3)$$

$$Gj \ge G_j^* \ \ , \forall j \dots \dots \dots \dots \dots (4)$$

Now objective function of system is

$$\sum_{c=1}^{c0} \sum_{j=1}^{N} p_j^s \, , c \le Pmax \dots \dots \dots \dots \dots (5)$$

In the equation M is factor of power, A and B is fairness factor and tradeoff of energy, D is interference of channel, E and F is assignment and SINR of secondary users (SUs)

Section 2

The cascaded machine learning algorithm is extension of machine learning algorithm. the process of cascading of machine learning increases the training samples of resource and mange the allocation process. The second phase of cascaded algorithm is control and optimize the energy efficiency of radio network.

Algorithm

The pairing of primary users (PUs) and secondary users (SUs) in MLP classifier as $X = \left[x_1, x_2, \dots, x_{N_l}, x_{N_l+1}, \dots, x_N\right] \in \ Channels$. Here paring of PUs/SUs represent as $x_i \in \ C0$. Now the power gain of K number of secondary users are$k_l = \{k_i\}_{i=1}^{N_l}$ the remaining N_u users $X_u = [X_{N_l+1}^u, \dots \dots \dots, X_N^u]$.

Step 1. Mapping of resource. The cascaded machine learning mapped the channel of cognitive radio network as

$$ni \in Pf(Pf)^n = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} \qquad\qquad (6)$$

For Xi, set of channel for training as

$$Xi = P(ni)\alpha \dots \dots \dots \dots \dots (7)$$

With ni the process of relation with derivation

$$di = \ \gamma_j \ \ j \frac{Xi}{G_{j,z}} \dots \dots \dots \dots \dots \dots (8)$$

Adjustment of weight of cascaded network

$$g_{j,z}\, di \times Wi \dots\dots\dots\dots\dots\dots\dots (9)$$

Summation of all resource of cognitive radio network.

$$RE = \sum_{j=1}^{N} \left\lfloor \frac{Gi}{Xi} \right\rfloor = \sum_{j=1}^{N} \lfloor wi \rfloor \dots\dots\dots\dots\dots..(10)$$

Minimize the energy factor of allocation

$$PE = min \sum_{z=1}^{Z^0} \sum_{j=1}^{N+1} Pf \dots\dots\dots\dots.(11)$$

$$s.t. \sum_{n=1}^{w} PE = Ni, \quad \forall j \qquad (12)$$

Step 2. Allocation of channel of secondary users

X(xi) $(i = 1,\dots,N + 1;\ z = 1,\dots,Z^0)$allocated channel

$$pridict\ Channel = \begin{cases} \sum_{k=1}^{k^{\ 0}} RE & i \\ +1 & otherwise \end{cases} \dots.(13)$$

$$PE = \begin{cases} R & if \sum_{j=1}^{N+1} \leq iteration \\ O & otherwise \end{cases} \dots\dots\dots\dots\dots\dots.(9)$$

$$\text{RA} = \left\{ \sum_{k=1}^{n} Fc + Cm + X(xi) \right\} \dots\dots\dots\dots\dots\dots\dots\dots.(14)$$

IV. Simulation Analysis

The proposed algorithm for CRN is simulated in MATLAB tools. The MATLAB tools provide communication tool functions and other functions of communication.the simulation process caried out in Windows 11 operating system, 16GB RAM and I7 processor. The simulation process considers one primary use base station (PBS) and K amount of SUs. The distance between PUs and base station is constant in all cases. The standard parameters used for simulation mention in table 1. The proposed algorithm compares existing algorithms such as RLA and ML. The performance of results measure in terms of average capacity and energy efficiency of CR [19,20,21].

Table 1 simulation parameters of Cognitive radio Networks

Parameters	Assigned value
Bandwidth	10MHZ
Resources	50

Transmission power (PUs)	40 db
Transmission power (SUs)	20db
SINR	10db
Interference threshold	5 X 10^{-10} w
Noise density	-110 db

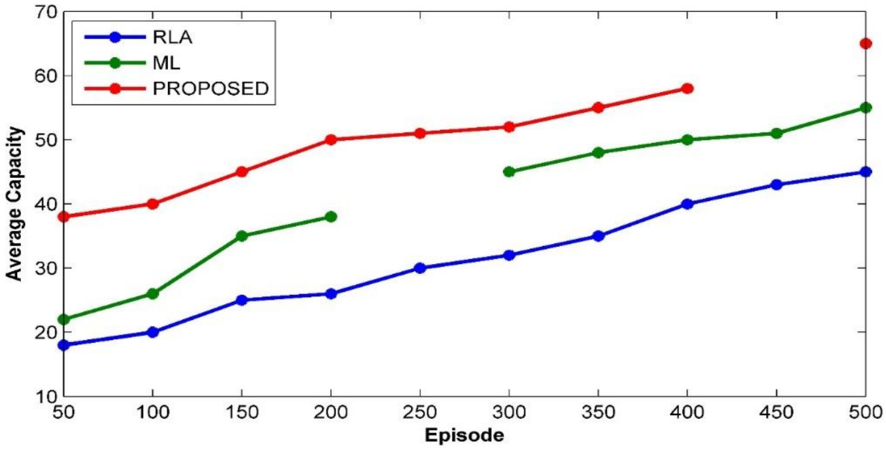

Figure 1: Performance analysis of average capacity using RLA, ML and proposed techniques with different number of nodes. Here we observe that the average capacity of proposed is better than RLA, ML.

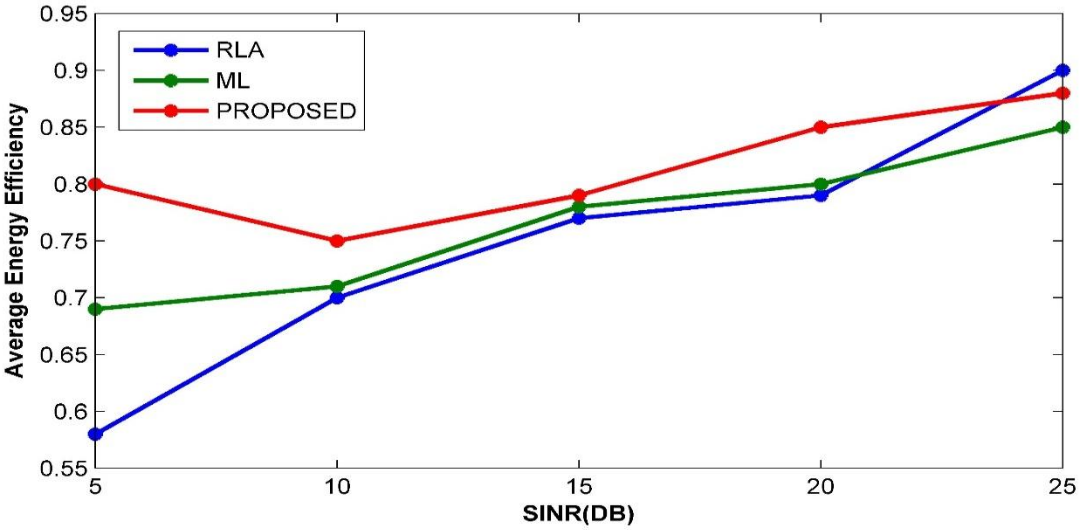

Figure2: Performance analysis of average energy efficiency using RLA, ML and proposed techniques with different SINR (DB). Here we observe that the average energy efficiency of proposed is better than RLA, ML.

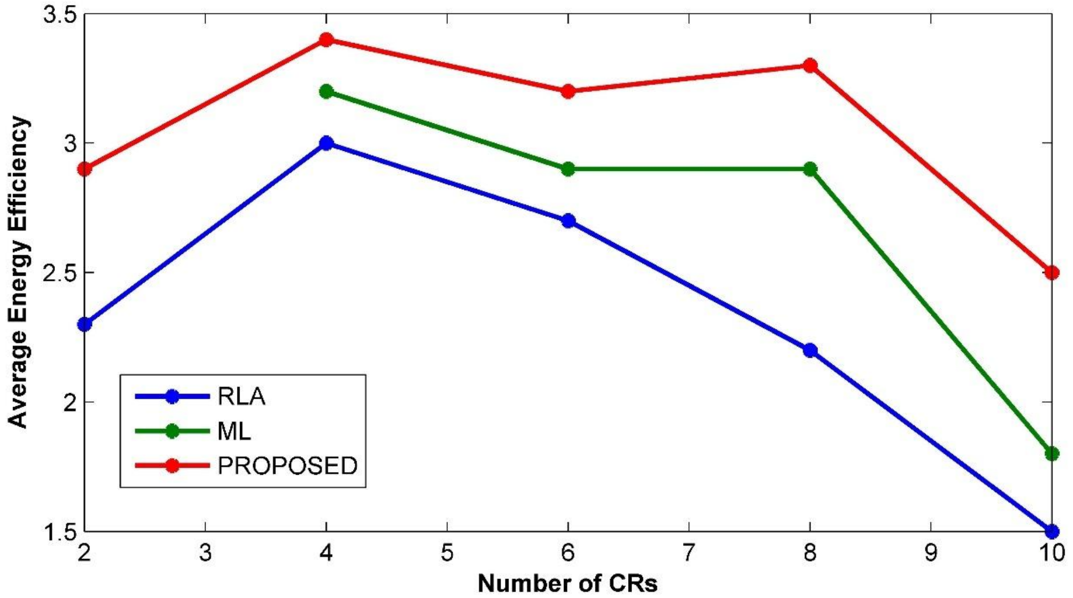

Figure 3: Performance analysis of average energy efficiency using RLA, ML and proposed techniques with different number of CRs. Here we observe that the average energy efficiency of proposed is better than RLA, ML.

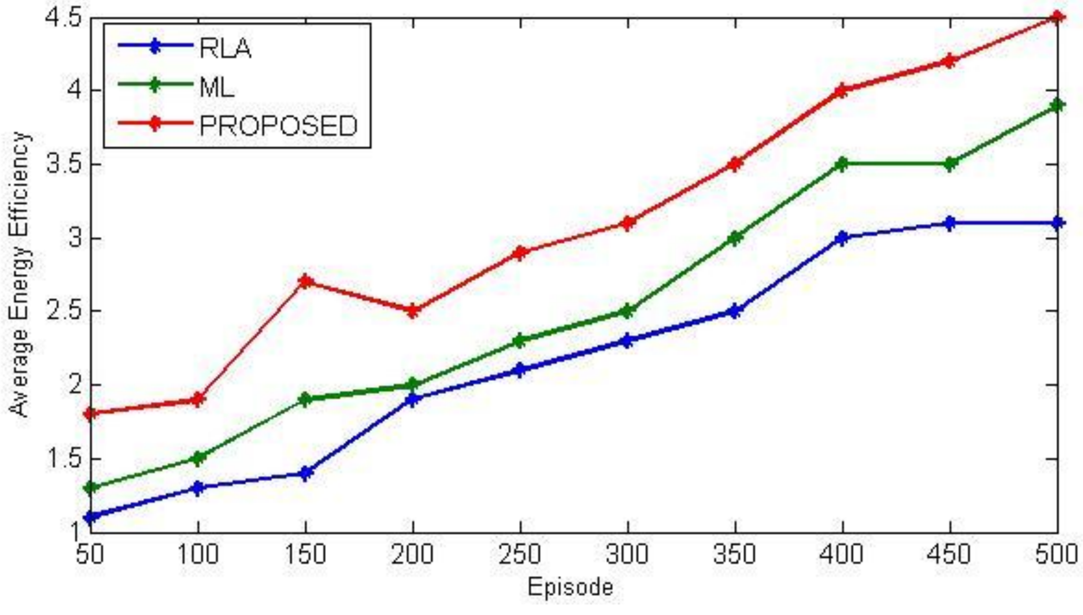

Fig 4: Performance analysis of average energy efficiency using RLA, ML and proposed techniques with different number of episodes. Here we observe that the average energy efficiency of proposed is better than RLA, ML.

V. Conclusion & Future Scope

This paper proposed cascaded machine learning algorithm for resource allocation and optimization in cognitive radio network. The algorithm applies on cognitive radio scenario in underlying mode of communication. the design algorithm processes the utilization of spectrum of primary users for secondary in limit of interference. Simulations are used to assess the performance of the proposed method, and the results are contrasted with those of existing RLA and ML algorithm. The findings shown that the cascaded algorithm achieves higher optimal resources when dealing with competing objectives. a cascading machine learning technique where the spectrum channels accessible changed with time and limits. We devised a cascaded machine learning resource allocation technique that combines an RLA method with ML mechanisms to address the energy-related issues. All of the objectives were satisfactorily balanced by our suggested solution, which also outperformed previous approaches in terms of convergence rate and level.

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