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Resource Allocation in Cognitive Radio Networks Based on Deep Learning Algorithm

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Abstract

In the next generation of wireless communication systems, resource allocation is crucial, particularly for cognitive radio networks (CRNs). Several approaches to resource allocation have been put forth in an effort to maximize CRN performance. However, since most wireless systems require precise and timely channel state information and/or other network statistics, putting these strategies into practice and achieving real-time performance in wireless systems is difficult. This paper presents a training method to train the neural networks and suggests a resource allocation strategy based on deep learning (DL). When compared to traditional resource allocation schemes, simulation results demonstrate the computational efficiency of our DL-based approach.

Keywords: - CRN, Wireless Communication, Deep Learning, Spectrum, Energy Efficiency

Introduction

Cognitive radio (CR) technology boosts the performance of wireless communication. In the mode of a cognitive radio network, secondary users (SUs) access the unused spectrum of primary users (PUs), provided that the use of the spectrum by the Sus does not interrupt the function operation of the Pus[1]. The processing of a cognitive radio network in three scenarios in a cellular communication network. underlayer cellular network, overlayer cellular network, and hybrid cellular network. In a cognitive radio network, there are two types of resources: energy and spectrum [2]. The optimisation and allocation of resources improve the performance of the cognitive radio network in terms of interference and selection of users. Deep neural networks (DNNs), also known as deep learning, have become more and more popular recently in a variety of fields, such as speech recognition and image classification [5, 6]. Researchers have also utilized deep learning technologies, including transmit power control [7], channel estimation [8], encoder/decoder design [9], and cognitive satellite communication in combination with reinforcement learning [10], in wireless communication research. As demonstrated by earlier research [8], [9], we can utilise DNN to exploit an ideal control strategy for communication systems without explicitly solving complex problems. Furthermore, a trained DNN model with a moderate number of layers is well suited for real-time operations due to its low computation time [7, 8]. These days, there are two popular methods for modelling and resolving the resource allocation issues for CRNs: optimisation theory and heuristic search. In order to obtain a near-optimal solution using the standard optimisation technique, the work in [11] investigated energy-efficient resource allocation in orthogonal frequency division multiplexing (OFDM)-based CRNs. This problem is transformed into a non-linear fractional programming problem employing a time-sharing method. The weighted sum-rate of orthogonally transmitting PUs is the goal of the algorithm in [12], which is formulated as a non-convex optimisation problem that is resolved by the primary and secondary networks' channel state information (CSI) and the Lagrange multipliers connected to the constraints. In [13], a non-convex objective function is used to represent an energy-efficient optimisation problem involving the resource assignment and power allocation for the OFDMA-based H-CRNs. The Lagrange dual decomposition method is used to derive closed-form expressions for this problem. Furthermore, the authors in [14] suggested utilising the modified ant colony algorithm—a metaheuristic approximation derived from the ant colony's foraging behaviour—to solve the resource allocation problem for CRN. The Particle Swarm Optimisation (PSO) algorithm is used to optimise a dynamic media access control (MAC) frame configuration and optimal resource allocation problem for multi-channel and ad hoc CRN [15]. This paper proposes a deep learning-based algorithm for the allocation of resources in a cognitive radio network. The proposed algorithm improves resource utilization and energy efficiency for secondary users. The proposed algorithm compares with existing algorithms like CNN and RL. The rest of the paper is organised as follows: in Section II, related work in the area of deep learning for cognitive radio; in Section III, proposed methodology for CRN; in Section IV, experimental analysis; and finally, conclusion in Section V.

II. Related Work

The author [1] proposes a resource allocation strategy in this study that aims to minimize the weighted sum of secondary interference power by balancing energy efficiency and spectrum efficiency (EE+SE). Our proposed resource allocation strategy in this study is based on a trade-off between energy efficiency and spectrum efficiency (EE+SE), with the goal of minimising the weighed sum of the secondary interference power. The author [2] proposes a CNN based on constellation diagrams to identify modulation modes such as 16QAM and 64QAM, which were difficult to discern in the previous CNN. In addition, a CNN based on constellation diagrams is made to identify modulation modes like 16QAM and 64QAM that were hard to discern in the previous CNN. This shows that QAM signals can be classified even in low signal-to-noise ratio-situational. The author [3] of the ACDL-Algorithm's Agent interacts with the network's environment in order to determine the optimal user-association and bandwidth-allocation policy. The ACDL algorithm's agent interacts with the network's environment in an effort to find the best user association and bandwidth allocation policy. The author [4] argues that by leveraging the empirical assumption that manufacturing heterogeneity among wireless transmitters, which conform to the same standard, results in unique and recurring signatures in each transmission, this technology can be utilized to identify and authenticate devices in a manner similar to a fingerprint. This technology can use the distinct, recurrent signatures produced by manufacturing heterogeneity amongst wireless transmitters that meet the same standard to identify and verify devices, just like a fingerprint. The author [5] trains the model using data produced by a genetic algorithm and verifies the accuracy of the suggested model in predicting solutions for resource allocation. We train the model first using the data produced by a genetic algorithm, and then we verify that the suggested model accurately predicts the solutions for resource allocation. According to simulation results, 86.3% of the time, the trained DL-Model can deliver the ideal solution. The author [6] states that, according to simulation data, our suggested method outperforms the ZF method and is more comparable to the MMSE method in terms of performance. According to simulation data, our suggested method performs better than the ZF method and is more comparable to the MMSE method in terms of performance. It also requires less computing time than the traditional method. The author [7] proposes the use of in-network deep learning and prediction to construct a "Deep Slice" model, which utilizes a Deep Learning (DL) Neural Network to control network availability and improve load efficiency. In this paper, we have used in-network deep learning and prediction to construct a „Deep Slice" model by using a deep learning (DL) neural network to control network availability and load efficiency. The author [8] discusses the algorithms of neural networks, support vector machines, and random forests. Neural networks, support vector machines, and random forests are these algorithms. We used the accuracy, miss detection, false alarm, and detection probabilities to compare and assess the performance of various algorithms. The author [9]: This study uses hybrid optimisation, a novel family of optimisation techniques. This will carry out an optimisation using two or more algorithms. The author [10] discusses recent developments in artificial intelligence for cognitive radio networks in this article. This article discusses recent developments in artificial intelligence for cognitive radio networks. The paper also classifies the methods offered based on the type of learning (supervised or unsupervised) and outlines the difficulties and applicability of each method in relation to the cognitive radio tasks. The author [11] proposes an approach where SUs communicate locally with their neighbours until the selection of the highest class of cluster heads and the creation of the appropriate clustering configuration. By using the suggested approach, SUs communicates locally with their neighbours up until the selection of the highest class of cluster heads and the creation of the appropriate clustering configuration. Measures of similarity between the SUs, which are chosen in accordance with the clustering process's goal, are used to analyse the messages. The author [12] proposes a theory supplemented by an Incremental Weights-Decremental Ratios (IW-DR) method based on priority-based scheduling. An Incremental Weights-Decremental Ratios (IW-DR) method based on priority-based scheduling supplements this theory. Regression models are employed in system reorganisation and efficiency enhancement. The author [13] introduced the ns3-gym-toolbox, which streamlines the application of reinforcement learning to networking problem-solving. In this work, we introduced the ns3-gym-toolbox, which streamlines the application of reinforcement learning to networking problem-solving.

The author [14] found that the simulation results indicate a reliability gain of 20.8% compared to the single connectivity approach. According to the simulation results, reliability gains over the single connectivity approach amount to 20.8%. When compared to the method of constantly configuring MC for devices, a 37.6% improvement is attained with high traffic loads. The objective of this research, as stated by the author [15], is to ensure the dependability of downlink communication in proactive vehicular networks with ultra-low latency through a unique radio resource allocation scheme. The objective of this research is to guarantee downlink communication dependability in proactive vehicular networks with ultra-low latency through a unique radio resource allocation scheme. The combined radio resource allocation scheme can achieve a data transmission success rate of more than 98% when the resource load rate reaches 40%. The author [16] used a DL-framework to study the design of resource-allocation algorithms for multi-channel cellular networks with D2-D communication. In this paper, we used a DL framework to study the design of resource allocation algorithms for multi-channel cellular networks with D2-D communication. Our goal was to maximise the D2D TPs' total SE while ensuring that legacy cellular users would receive a minimal data rate. The author [17]. This has happened as a result of the numerous high-frequency devices that require substantial quantities of available bandwidth. This rising demand has led to the invention of cognitive radio networks to accommodate this increased demand. The author [18] proposes an optimal Road Side Unit (RSU) selection technique for Handoff in this study. In this study, an optimal roadside unit (RSU) selection technique for handoff is proposed. Reinforcement learning based on the MDP (RL-MDP) has been found to have a 13% lower decision delay for selecting the best RSU when compared to the current handoff schemes. The author [19] This study covers the architecture, use, and applications of machine learning (ML) for resource management in multibeam GEO-satellite systems. The author [20] An uncertainty-aware DL model for real-time change detection in the CU distribution and robust wireless CU prediction are provided in this study. Using BNNs, we have employed an encoder-decoder-framework-based DL model to account for the uncertainty in the model.

III. Proposed Methodology

This section describes the proposed methodology of resource allocation in a cognitive radio network. Figure 1 shows a system model of a cognitive radio network. The proposed algorithm modifies a hidden markov network. The modified HMN is compact and feedforward. The proposed algorithm is a 3-layer deep network. The process of an algorithm is described here[12,14].

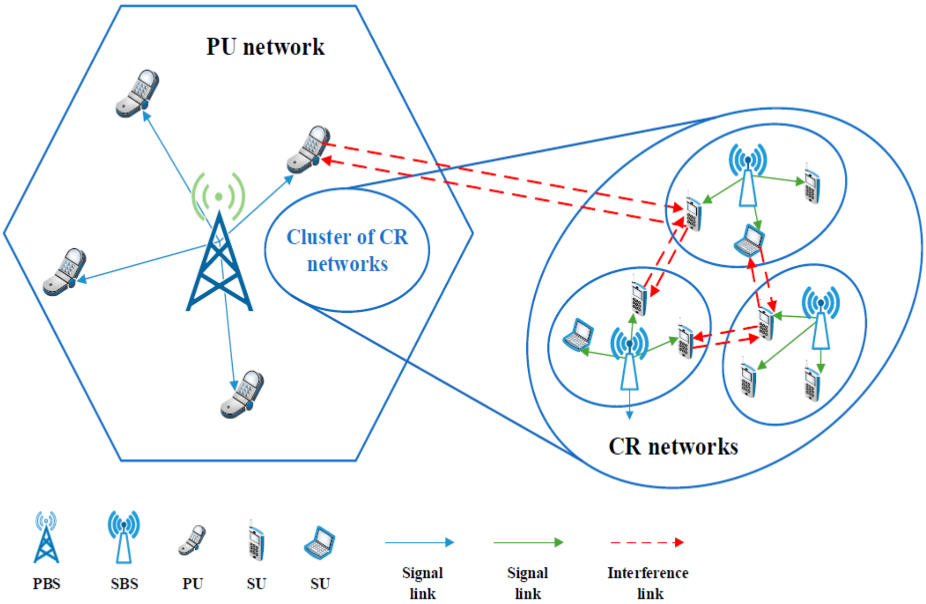

Figure 1 system model of primary users and secondary users

the allocation of resources of secondary users, the total available resources are

$Rij(x) = wijT\emptyset(x) + Kij$.................. (1)

The segmentation of spectrum of primary users

$Si = \{x|Rij(x) > 0, j = 1,2, \dots \dots . . n, j \neq i\}$....................... (2)

If x is RF and Ri is resource distribute X into RF I is x is not in Ri(i=1,2,………,n) is distributed RF load

$Li(x) = \sum_{i\neq j,j=1}^{n} sign(Rij(x))$…………………….. (3)

Where $sign(x) = \begin{cases} 1\ for\ x \geq 0, \\ -1\ for\ x < 0, \end{cases}$

And x is categorized into different load condition, overload and under load

$\arg \begin{matrix} \max Li(x) \\ i = 1,2, \dots, n \end{matrix}$..................................... (4)

If x ϵ RiLi(x) =n-1 and L(x)<n-1

A markov decision process is tuple (S, A,P,R,Z) define as

S is a finite set of states

A is finite set of actions

P is a state transition probability matric

R is reward function

Z is constraints factor, Z ϵ[0,1]

$T_s^O = T[S_{t+1} = s|S_t = s, A_t = a|$ ....(5)

Equation (5) is state of overload of RF

$$T_s^u = T[R_{t+1}|S_t = s, A_t = a|\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Equation (6) is reward function state of underload condition.

$$I(\frac{O}{U}) = T[A_t = a|S_t = s]\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Euuation (7) is function of ideal load in RF condition

Now reward point of state is

$$R_s^I = \sum_{a\epsilon A} I(\frac{O}{u})R_s^a\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Xt is decayed sum of all rewards in markov reward chain form time t towards. The formulation of decay is

$$X_t = R_{t+1} + ZR_{t+2} + A.A.A = \sum_{k=0}^{\infty} Z^k R_{t+k+1}\ldots\ldots\ldots\ldots(9)$$

Now that measure the maximum utilization of queue to control RF congestion, the maximization of resource expressed as

$$Q(N) = E[X_t|S_t = s\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

According to state information environment, we can find the optimal maximum RF behaviours function

$$L(a|s) = \{\ 1\ if\ a =\ argmaxN(s,a), a\epsilon A\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

IV. Experimental 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 CNN and RL. The performance of results measure in terms of average capacity and energy efficiency of CR [18,19,20].

Table 1 Simulation parameters of Cognitive radio Networks

Parameters	**Values**
Simulation area	1000 x 1000 m
Number of users	100,200,300,400, and 500
User mobility	10 m/s
MAC	IEEE 802.11n physical
Transmission range	250 m
User transfer power	17dBm
Base station transfer power	20 dBm
Bandwidth	20 MHz
Traffic source	Constant bit rate (CBR)
Packet size	1024 bytes
Number of frames per packet	5 frames
Simulation time	200 s

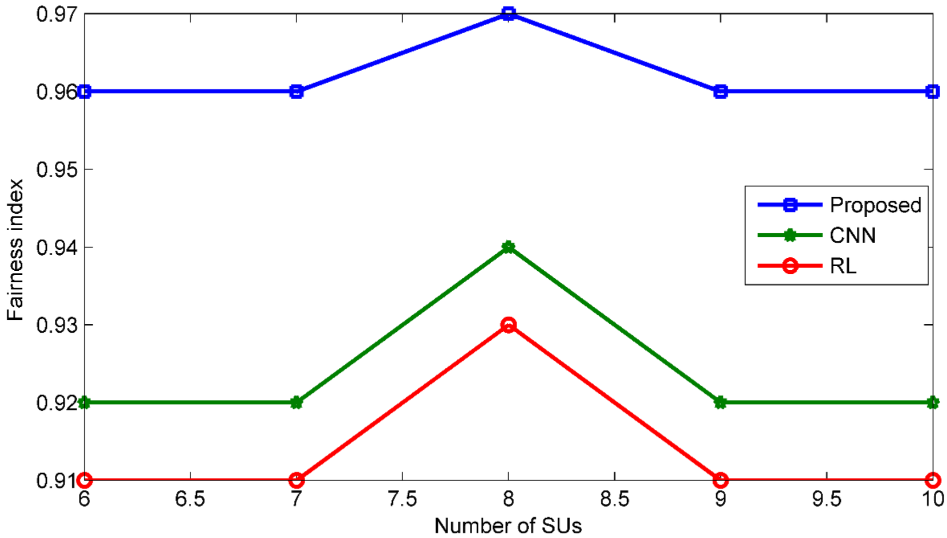

Figure 2 Comparative performance of result analysis of proposed, CNN, and RL, using method of Fairness index and Amount of SUs. Here we can see that the value of proposed is better than CNN and RL, that is ,the value of proposed is more which is 0.97 and the value of CNN which is more is 0.94 and that of RL is 0.93 in this we can see that the result is better.

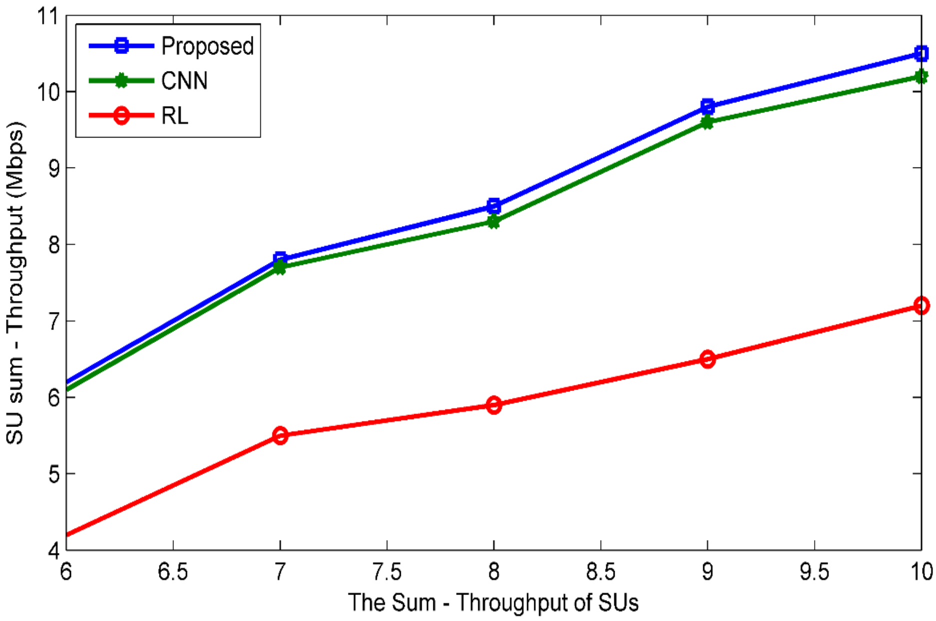

Figure 3 Comparative performance of result analysis of proposed, CNN, and RL, using method of SU sum- Throughput (Mbps) and The Sum - Throughput of SUs. Here we can see that the value of proposed is better than CNN and RL, that is, the value of proposed is more which is 10.5 and the value of CNN which is more is 10.2 and that of RL is 7.2 in this we can see that the result is better.

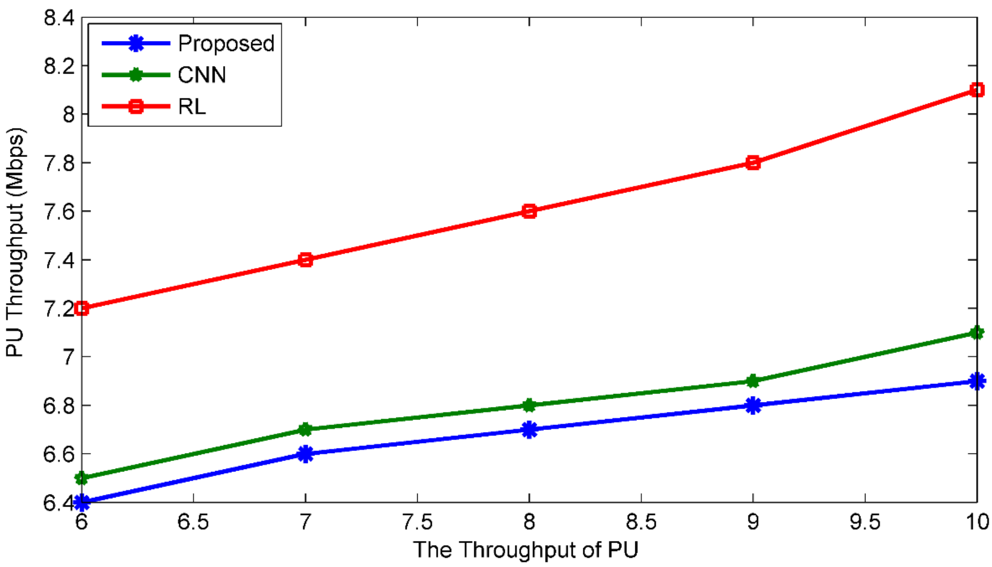

Figure 4 Comparative performance of result analysis of proposed, CNN, and RL, using method of PU Throughput (Mbps) and The Throughput of PU. Here we can see that the value of RL is better than CNN and proposed, that is the value of RL is more which is 8.1 and the value of CNN which is more is 7.1 and that of proposed is 6.9 in this we can see that the result is better.

V. Conclusion & Future Work

In order to maximise data rate for all SUs and ensure QoS for PUs, we proposed a channel selection and power adaptation scheme for the underlay CRN in this paper. In order to investigate the best resource allocation plan, we used the DL framework. The random walk model is used in this framework to simulate user movements, and the environment of the undelay CRN is modelled as dynamic graphs. Additionally, the CNN extracts the important interference features from the created dynamic graph. In order to prevent the split with mismatched features and tasks, an end-to-end learning model was also created to implement the following resource allocation task. The theoretical analysis was confirmed by the simulation results, which also demonstrate the stable convergence performance of the suggested algorithm. The results of the experiments demonstrate that the suggested algorithm is capable of greatly enhancing the data rate of CR networks and guaranteeing the QoS needs of PUs.

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