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Distribution of Heterogeneous Traffic Resources for 5G Cognitive Radio Networks based on Cooperative Learning and QOE

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Abstract— In addition to offering faster speeds and lower latency, 5G networks provide enhanced availability, significantly higher capacity, improved stability, and superior connectivity. The Mean Opinion Score (MOS), which quantifies the subjective quality of the user experience, has emerged as a widely accepted metric for assessing the quality of various types of network traffic. As we move towards the 5G era, measuring end-user quality has become increasingly important in the evolution of wireless communications. This paper presents a resource allocation approach for 5G cognitive radio networks that leverages cooperative learning and prioritizes Quality of Experience (QoE) for integrated heterogeneous traffic. The solution is based on a distributed underlay Dynamic Spectrum Access (DSA) system that utilizes MOS as a foundational metric for managing resource allocation across real-time video and data traffic, each with distinct characteristics. The proposed technique is designed to meet strict interference limitations for primary users while simultaneously maximizing the overall MOS. This is accomplished by employing reinforcement learning in a system where primary users and secondary users share the same frequency band of interest, ensuring efficient coexistence. Importantly, MOS serves as a standardized measure that allows for training across nodes carrying various types of traffic without compromising performance.

Keywords: 5G (Fifth Generation) Mean Opinion Score, Dynamic Spectrum Access and Quality of Experience.

I. INTRODUCTION

Numerous smart gadgets are getting more and more popular due to the quick advancement of communication technology. The mobile phone industry is also expanding quickly, and the wireless network's storage capacity is also rising quickly. At the same time, numerous new service requirements and features are being enhanced, and dependability, speed, and latency are being held to higher standards. The optimization and design of next mobile communication networks will now face new challenges [1]. The capabilities of the fifth generation (5G) are anticipated to manage users in accordance with their requirements, which might be services or apps. Providing diverse user groups with their desired transportation services calls for effective technology that uses little money and energy [2].

Past iterations of mobile phone communication technology have proven inadequate in meeting the evolving demands of future communication. This inadequacy is primarily attributed to the ever-expanding variety of communication services, the relentless surge in network traffic, the continuous proliferation of terminal devices, and the escalating data transmission speeds required by users. Due to the numerous end users and varied requirements in today's rapidly developing 5G, it is crucial to accomplish efficient resource allocation with the goal of satisfying customers' requests [3].

The Internet of Things (IoT) is supported by the fifth-generation mobile network (5G), which also uses mobile devices to process massive amounts of data. With this capability, we discover a unique cooperative communication idea that accommodates high energy consumption mediums, heterogeneous networks, huge channel accessibility, and complicated interference environments through high signal coverage and capacity among mobile devices [5]. Resource allocation strategies that accomplish effective interference control, resource scheduling, and user matching are at the heart of cooperative communication systems. The widespread adoption of devices, applications, and services has elevated consumer expectations and placed greater demands on network service providers in terms of delivering quality of service (QoS). [4]

An upcoming technology called the cognitive radio sensor network (CRSN) promises to greatly expand the use of wireless sensing applications. Ideal sensor nodes coexist with more capable many gadgets in a typical CRSN. Numerous sensor nodes and at least one sink node make up the CRSN. Those nodes have CR capability on some or all of them. [5]

II. LITERATURE REVIEW

The two primary categories of resource allocation methods for wireless networks are distribute-based and central-based, where the sink node is in charge of making the choice. The latter form allows each unit to choose the resources it can use. You can make the choice with or without the support of other units. The resource allocation plan is generally linked to QoS assurance since it needs to be effective in order to meet QoS criteria. Power, scheduling, and channel assignment are the most important components, even if the resource allocation components may differ from scheme to scheme. The key distinction between these systems lies in their approach to channel allocation. In DCA, channel reallocation is a frequent occurrence, allowing for dynamic adjustments, whereas FCA relies on static channel allocation that cannot be modified once established [6].

Most studies now in existence only operate in radio settings that are identical to one another, or in radio circumstances that are exploited channels. By controlling the conflict between Primary Users (PUs) and Secondary Users (SUs), QoS provisioning may be accomplished. In these circumstances, the SUs are given the right amount of channel bandwidth and transmission power to maintain their QoS levels without causing the PUs undue disturbance. The resource allocation for 5G cognitive radio networks using cooperative learning and QoE-Driven integrated heterogeneous traffic is given in this paper. In this research, numerous SUs are taken into account while accessing a single spectrum band to transmit ordinary data traffic or real-time video. The remainder of the writing is structured as follows: The Literature Survey is described in Section II. Cooperative learning based QoE-Driven integrated heterogeneous traffic resource allocation for 5G cognitive radio networks is presented in section III. [7]

In the realm of 5G networks enriched with edge computing capabilities, the focal point revolves around the implementation of intelligent traffic-adaptive resource allocation. This endeavor predominantly hinges on harnessing artificial intelligence to efficiently manage the flow of mobile traffic. Our approach initiates with the development of a predictive algorithm tailored for traffic flow analysis, leveraging the power of Long Short-Term Memory (LSTM) models, further enhanced by an attention mechanism. This algorithm is adept at training on single-site mobile traffic data, enabling it to provide highly accurate forecasts of traffic flow peaks. To extend the applicability of our solution, we introduce a sophisticated IoT-based architecture designed to predict and control mobile traffic across multiple sites seamlessly. This architecture exhibits the ability to dynamically allocate communication and computation resources as needed, optimizing network performance. In comprehensive testing scenarios, our proposed methodology demonstrates its efficacy by significantly reducing packet loss ratios and minimizing communication latency. [8]

Allocating resources in diverse cognitive radio sensor networks. In order to address multilayer heterogeneity in cognitive radio sensor networks, an effective resource allocation protocol, enhanced Pliable Cognitive Medium Access Protocol, is developed. The variety of network applications makes up the first level, while the radio environment makes up the second level. The suggested plan tackles concerns with scheduling and radio channel distribution. While spectrum sensing is spread, decision-making about allocation is centralized, improving efficiency and reducing interference. The success of the suggested strategy also involves enhancing the possibility to exploit a larger range of the radio spectrum, notwithstanding the sensor networks' restricted capabilities. In the next 5G of wireless networks, the improved Pliable Cognitive Medium Access protocol is particularly suitable for crucial communications that attract attention. The strong performance of the proposed method is demonstrated by simulation results and by comparing it to other protocols. [9]

In the context of IEEE 802.11 cognitive Wi-Fi networks, a sophisticated resource allocation technique has been developed. Its efficiency is achieved by taking into account the state of transmission channels and traffic conditions. To improve the precision and effectiveness of the algorithm under discussion, a Markov chain model-based approach is employed to predict potential network throughput. Furthermore, in the channel allocation process, an ARMA model-based approach is utilized to forecast traffic peaks, adding an additional layer of accuracy and efficiency to the resource allocation procedure [10].

Establishing a highly adaptable and changeable architecture that takes into account contextual and content-related information is crucial when it comes to creating the infrastructure for 5G networks. These precise specifications have been rigorously addressed by the Flex5Gware network design. In addition, we explore the nuanced interactions between adaptability, reconfigurability, context awareness, and content awareness. This investigation clarifies how two key elements of the Flex5Gware architecture, namely dynamic multi-cell coordinated resource scheduling and on-the-fly MAC reconfiguration, might use contextual and content-related data to guide their reconfiguration decisions. Comprehensive analyses, involving both prototype and simulation, show significant benefits, such as enhanced cohabitation across various access networks and decreased latency.

III. COOPERATIVE LEARNING BASED QOE-DRIVEN INTEGRATED HETEROGENEOUS TRAFFIC RESOURCE ALLOCATION

For 5G cognitive radio networks, cooperative learning-based integrated heterogeneous traffic resource allocation is described. In the works, QoE provisioning in CR systems with multiple antennas was the main topic. While developing closed form formulations for three QoE metrics, attention was only paid to SU satisfaction from a latency standpoint. To improve video transmission quality over time. In this study, we address the case where numerous SUs use a single spectrum band to provide ordinary data or real-time video.

A main network (PN) and a secondary network (SN) of wireless networks are what we presume to exist. Under the usual underlay DSA approach, the PN with a single primary link shares a single channel with the SN at a certain time instant. The SN provides service to N SUs dispersed throughout a secondary base station (SBS). Adaptive modulation and coding (AMC) is the transmission method used by all secondary and primary

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lines. To meet the interference demands from the PU and the other SUs, each SU modifies its broadcast settings. Regular data and real-time/streaming video are transported via the SN connections. With additive white Gaussian noise, it is assumed that the transmission channel is quasi-static.

The SINR for the ith SU at its associated SBS, SINR(s), and the SINR at the principal base station (PBS), SINR(p), are both given as

$$SINR^{(p)} = \frac{G_0^p P_0}{\sigma^2 + \sum_{j=1}^{N} G_j^{(p)} P_j} \quad (1)$$

$$SINR_i^{(s)} = \frac{G_0^{(s)} P_i}{\sigma^2 + G_0^{(s)} \sum_{j\neq 1}^{N} G_j^{(s)} P_j} \quad (2)$$

Where,
P0 is the PU transmit power, which is a fixed number,
Pj is jth. SU's transfer power,
G0 (p) is the channel gain between PU and PBS and
Gj (p) is jth.

SU's channel gain to the PBS, G0 (s) is the channel gain between PU and the ith. SBS, ri (s) is the ith. SU's transfer rate, Pi is the ith. SU's transfer power, Gi (s) is ith. SU's channel enrich, while is the sound power. We apply the following limitations on secondary and main SINRs in order to achieve the underlying DSA and QoE goals:

$$\begin{Bmatrix} SINR^{(p)} \geq \beta_0 \\ SINR_i^{(s)} \geq \beta_i, i = 1, \ldots . . N. \end{Bmatrix} \quad (3)$$

The primary and secondary SINR thresholds, respectively, are β0 and βi. The allotted transmission power for each SU may be determined by using the same assumptions for both SINR restrictions.

$$\begin{Bmatrix} P_i = \frac{\Psi_t(\sigma^2 + G_0^{(s)} P_0}{G_t^{(s)}(1 - \sum_{j=1}^{N} \Psi_j)}, i = 1,2, \ldots, N, \\ \Psi_i = (1 + \frac{1}{\beta_t})^{-1} \end{Bmatrix} \quad (4)$$

Equation (3) may be rewritten as, once the SU powers derived from (4) are substituted in (1).

$$\sum_{j=1}^{N} \alpha_j \Psi_j \leq 1 \quad (5)$$

Where

$$\alpha_j = \frac{G_j^{(p)}(\sigma^2 + G_0^{(s)} P_0)}{G_j^{(s)}(\frac{G_0^{(p)} P_0}{\beta_0} - \sigma^2)} + 1 \quad (6)$$

Since β0 is taken to be a constant, each SU must modify βi in order to satisfy equations (4) and (5). By adjusting the transmit bit rate, this modification may be made. The relationship between transmit bit rate and the SU threshold SINR may be expressed as follows, based on the study for the system setting under consideration:

$$r_i^{(s)} = W log_2(1 + k\beta_i) \quad (7)$$

Where k = 1:5/ln(5BER) is a constant that refers to a desired maximum transmit bit error rate (BER) requirement and M(βi) = (1 + kβi) displays the amount of bits per modulation symbol and practically only accepts a small number of integer values. This is the given underlying DSA scheme work. To collectively fulfill the SINR βi requirements in (3) and (5), each SU chooses its target SINR and ri (s) correspondingly. The modulation scheme is altered by altering and the appropriate ri (s).

The goal of our optimization challenge is to optimize the network performance measure while ensuring that the primary user's total interference requirements are satisfied. As we approach the 5G era, QoE is receiving a lot of attention as the representation of end-user focused quality evaluation. As a result, we chose QoE as the network performance parameter to evaluate the traffic quality supplied. The most used statistic for modeling the QoE of delivered traffic is MOS, which is one of the metrics used to estimate QoE. The network is then adjusted based on the average quality of experience (QoE) of all video and data sessions sent by SUs. The MOS formulae that are used in this study to quantify the quality of supplied data and video traffic are provided in the section that follows.

MOS model for data, the following is how the MOS for data flow is determined:

$$Q_D = \alpha log_{10}\left(b r_i^{(s)}(1 - p_{e2e})\right) \quad (8)$$

The end-user's perceived maximum and lowest levels of data quality are used to derive the parameters a and b. When a user's transmit rate is R and their effective receive rate is similarly R, packet loss is eliminated and the end-user's quality perception rate should be at its maximum, or 5. While a minimum transmission rate is given a MOS value of 1. In this task, the times are 1:3619 and 0:6780.

Peak signal-to-noise ratio (PSNR), a widely used statistic for evaluating the quality of video, may be used to accurately gauge a movie's coding efficiency. But it is well known that PSNR does not precisely match how subjectively people judge video quality. Find a survey of video quality evaluations in. One method suggested a simple linear mapping between PSNR and MOS, as illustrated in Fig. 1. Several strategies have been presented to measure user satisfaction for video applications. According to this, MOS value is assigned as 4.5 for PSNR of 40 dB and 1 for PSNR of 20 dB.

The limits arise from the fact that quality degradations below 20 dB are relatively noticeable and that video sequences with a PSNR of 40 dB or higher can scarcely be distinguished from those that have been broadcast. The relationship between MOS and an objective measure of visual distortion has a sigmoid pattern, according to the ITU-R BT.500-13 standard. According to Table I, the work provided the heuristic mappings from PSNR to MOS.

$$Q_V = \frac{c}{1 + \exp(d(PSNR - f)} \quad (9)$$

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QV is the MOS for video, while c, d, and f are the inputs to the logistic function. When the learning agent notices its current state, s2S, it reacts by doing one (or more) actions that, when followed by a set of rules, produce a scalar instantaneous reward (R(i)t). The difficulty is in identifying a strategy that maximises the received discounted reward V with a discount factor of (0 < ϒ < 1). Each SU selects an approach from A(i), modifies its transmit power and other pertinent transmission parameters at the same time, and then monitors changes to the system and its own transmission.MOS has been utilized as a QoE metric since it offers a standard quality evaluation statistic for all types of traffic. The actions that each SU must do in order to accomplish the unique learning process are outlined in Algorithm 1. It should be noted that the method will first undertake an initial exploration phase, when each Q-table item is visited once, followed by an exploitation phase, due to the initialization for all the SUs being set to Qi0 = 0.

A Q-table that contains the reward for each action is created (learned) iteratively using the Q-learning algorithm. Each Cognitive SUs first becomes aware of its surroundings, moves on to the action associated with the biggest reward, runs the Q-learning algorithm to acquire the reward of the chosen action, and then updates its Q-table depending on the immediate reward it has just got. The Q-table will therefore demonstrate how the activities impact the wireless environment. Restarting the cycle of cognitive and ignoring the environmental information gathered by other SUs already present in the system is inefficient since when an SU enters the already taught system, this environment shows no evidence of change.

Thus, in order to save learning time and improve learning results, the new joint SU may be taught this environmental awareness that is indicated in the Q-table. The term "docile radio" applied to this radio paradigm. In contrast to CR, didactic radio prioritises teaching above learning. According to the distributive paradigm, nodes having more "experience" in handling a specific system problem would train less competent nodes, speeding up learning. Because of this, we propose a docitive technique in which the new SU initialises its Q-table by averaging the Q-tables from the current users, while the SUs currently present in the network initialise their cognitive cycle using their own Q tables that they had previously learnt by employing Algorithm 1.

Algorithm 1 Individual learning for resource allocation

Initialization: $Q_0 = 0$ for all the SUs
  for time $t < t_{\max}$ **do**
    for all SU_i, $i = 1, \cdots, N$ **do**
      Select the action $a_t^{(i)} = \arg\max_{a_t^{(i)}} Q(s_t^{(i)}, a_t^{(i)})$
      Update the state $s_{t+1}^{(i)}$ (10), (11) and the reward $R_t^{(i)}$, (14).
      Update Q-value $Q_t^{(i)}(s_t, a_t)$, (15).
    end for
  end for

The impacts of initializing the Q-table of the combined SU on learning performance are examined in the next section by averaging the Q-tables from SUs with comparable and diverse traffic kinds.

$$Q_c = \frac{1}{N}\sum_{i=1}^{N} Q^{(i)} \quad (10)$$

The mentioned docitive mechanism is shown in Algorithm 2.

Algorithm 2 Cooperative Learning (Docition)

  (Run as a new SU joins the network)
  Add one new SU as SU_{N+1} and initialize $Q_0^{(N+1)}$ with Q_c following (17).
  for all SU_i, $i = 1, \cdots, N+1$ **do**
    Restart individual learning (Algorithm 1) with the existing $N+1$ Q-tables.
  end for

Furthermore, a network novice (node with less experience) is considered to be indicated via a low bit rate control channel.

IV. RESULTS AND DISCUSSION

MATLAB is used to build cooperative learning-based QoE-Driven integrated heterogeneous traffic resource allocation for 5G cognitive radio networks. The findings indicate that compared to the individual learning algorithm, the docition algorithm (Algorithm. 2) may roughly lower the average number of iterations needed to reach convergence by 2/3. With the exception of the variance in the number of partners chosen to learn from, all five of the most recent systems employing cooperative learning performed almost as well as those using doction. The average MOS of the secondary network at the convergence point is depicted in Fig. 1 as a function of the total number of SUs in the SN.

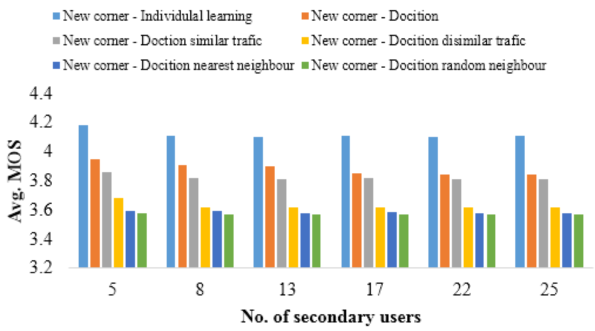

Figure 1. Avg. MOS in SN

It is clear that as the number of SUs rises, the average network MOS falls. The reason for this is because each SU tends to converge in a less SINR value as the number of users rises in order to fulfil the interference limitations, which ultimately leads in a less average MOS. This result shows that our QoE-driven resource allocation strategy consistently delivers high MOS values, even with 25 SUs present in the network. It is also evident that all systems function equally well in terms of MOS, and this is due to the fact that MOS also makes it easier for some CR nodes to communicate with one another and transfer different types of traffic to and from one another.

The constancy of the relationship between rewards and wireless states and actions is a pivotal aspect in understanding the dynamics of network performance. Even as the specific Mean Opinion Score (MOS) values for distinct types of network traffic may undergo alterations over time, the fundamental

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relationship between the rewards acquired for different wireless states and actions remains intact. This persistence can be attributed to the inherent nature of MOS and the calculation methodology that consistently relies on monotonically increasing functions of objective quality measures or Quality of Service (QoS) values. The tangible implications of this enduring relationship are illustrated in Figure 2, where the congestion rate is graphically depicted in relation to the number of Secondary Users (SUs) within the network. This figure serves as a visual testament to how the network's congestion behavior remains tied to the rewards structure, highlighting the network's ability to adapt and maintain certain performance characteristics even as traffic patterns evolve and user counts fluctuate.

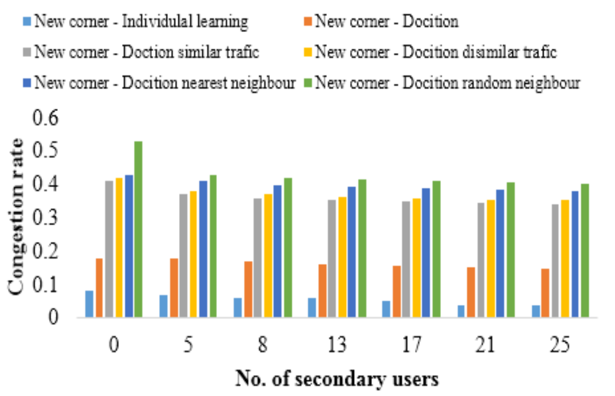

Figure 2. Congestion rate

Fig. 2 plays a pivotal role in shaping simulation choices regarding the number of Secondary Users (SUs) within a network while maintaining a predefined system congestion rate. This figure serves as a valuable reference point for decision-making. When employing the cooperative learning solution, it becomes apparent that the system can accommodate more users if it is determined that the secondary network can effectively operate at the designated congestion rate. This adaptive approach enhances the network's efficiency, ensuring that resources are optimally utilized without compromising performance. In addition to network resource allocation, the significance of Fig. 2 extends to the realm of cooperative learning, as showcased in Fig. 3. This figure vividly illustrates how adopting a docitive paradigm, which facilitates the transfer of knowledge from newcomers to experienced peers, leads to a significant reduction in the number of iterative rounds needed to achieve convergence. Remarkably, the utilization of this paradigm outperforms individual learning algorithms by reducing the convergence time by up to 65%. This highlights the remarkable efficiency gains and accelerated learning curve made possible through cooperative and docitive learning approaches.

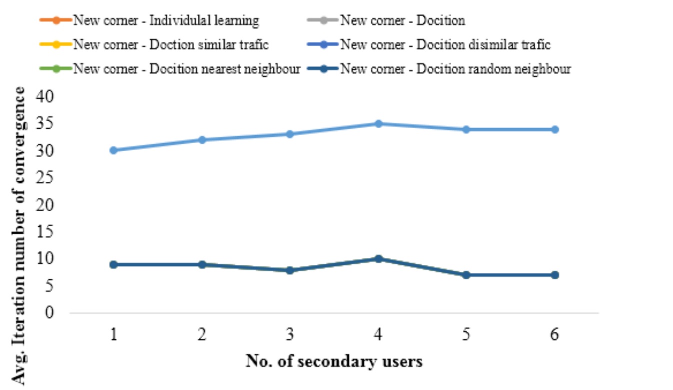

Figure 3. Average no. of cycles at the convergence point

V. CONCLUSION

This paper introduces a cooperative learning-based approach for resource allocation in 5G cognitive radio networks, addressing the integration of heterogeneous traffic. The paper outlines an underlay Dynamic Spectrum Access (DSA) technique designed to meet interference constraints on primary user (PU) transmissions while allowing secondary users (SUs) to adapt their transmit power, modulation schemes, and transmit rates. The primary objective is to maximize the average Quality of Experience (QoE) across all traffic types, including real-time video and regular data traffic. Mean Opinion Score (MOS) is employed as a unified metric that offers a standardized measurement scale for assessing the quality of various traffic types. This not only caters to the quality evaluation requirements of end-users in 5G networks but also facilitates the seamless integration of diverse data streams. Notably, MOS enables the study of interactions between nodes carrying different traffic types, marking a significant advancement in performance evaluation. Simulation studies demonstrate that all systems perform comparably well in terms of MOS. This outcome is attributed to MOS's ability to foster communication between specific cognitive radio (CR) nodes involved in transmitting various types of traffic to and from each other.

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