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Cloud-Enabled Geo-Location Based Qos-Centric Spectrum And Channel Allocation Framework For Cognitive Radio Networks

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Abstract
The rapid expansion of the wireless communication systems is increasing the demand for an efficient spectrum utilization. Conventional fixed spectrum allocation policies are often causing the spectrum scarcity even when the significant portions of the spectrum are remaining underutilized. Cognitive Radio Networks (CRNs) is addressing this challenge by allowing secondary users in opportunistically accessing the unused spectrum without interfering with the primary users. However, the dynamic and heterogeneous nature of the wireless environments is creating the significant challenges in maintaining the Quality of Service (QoS). The cloud computing and geo-location awareness is providing newer opportunities for an intelligent spectrum management because this is supporting the centralized monitoring and the data processing capabilities. Despite significant advancement in the cognitive radio research, where various limitations are remaining in conventional spectrum allocation techniques. Many of the methods are focussing primarily on maximizing the throughput without considering the influence of the channel availability and interference. In this paper, we propose a cloud-enabled geo-location with the QoS-centric spectrum and channel allocation framework for a cognitive radio networks. The proposed architecture is combining four cooperative modules that is including the spectrum sensing, resource awareness analysis, QoS-centric channel allocation, and policy-controlled spectrum access. The spectrum sensing module is monitoring continuously the licensed and unlicensed frequency bands, and it is reporting the channel availability. The resource awareness layer is aggregating the traffic demand, the node state information, the channel quality indicators, and the interference levels that are processed within the cloud platform. A QoS-centric channel allocation mechanism is evaluating the metrics, and it is assigning the priority scores to the available channels. The spectrum access controller is verifying the regulatory policies and dynamically is reallocating the channels when the primary user activity is detected. The proposed method is achieving a spectrum utilization efficiency of 94.3%, which is performing better than the conventional allocation approaches. The system is achieving a QoS satisfaction ratio of 92.6%, which is indicating the reliable service delivery for a heterogeneous user requirement.

Keywords Cognitive Radio Networks, Cloud-Enabled Spectrum Management, Geo-Location Awareness, QoS-Centric Channel Allocation, Dynamic Spectrum Access.

Introduction

The growth of the wireless communication services is increasing the demand for an efficient spectrum utilization in the modern communication systems. The conventional spectrum allocation policies are relying on the static licensing mechanisms that is assigning the frequency bands to the service providers [1]–[8].

Despite these advancement, cognitive radio networks still is facing the technical challenges that tends to limit the large-scale deployment. One of the major challenges is involving an accurate spectrum sensing because the secondary users must reliably detect the presence of primary users before the assessment of a channel [9]–[13].

Conventional spectrum management frameworks attempt to is addressing these challenges through the optimization techniques. However, many of the methods are focussing on maximizing the throughput or improving the spectrum utilization without considering the geographical distribution of the cognitive radio nodes and the spatial characteristics of spectrum availability [14].

Apart from the challenges associated with spectrum sensing and QoS management, security is an issue of concern in the context of cloud-enabled cognitive radio networks. With the introduction of cloud computing, there are concerns of unauthorized access to spectrum usage information, tampering of data in aggregate sensing reports, and compromising the centralized allocation process through denial-of-service attacks. Moreover, there is the issue of new attack surfaces, which in this case would be associated with malicious secondary users who would use the signals of primary users to force unnecessary vacating of the channel, which is known as primary user emulation attack. With the use of geo-location information, there is also a concern of privacy, considering that the tracking of node positions could be used maliciously.
Therefore, the objective of this research is involving in designing and implementing the cloud-enabled geo-location based spectrum and the channel allocation framework that is improving the QoS in the CRN.
The novelty of this work lies in the combination of geo-location awareness with the cloud-enabled QoS-centric channel allocation strategy that is supporting the intelligent spectrum management in the CRN.
This research contributes two major components to the field of the cognitive radio spectrum management. The first contribution is involving the development of a novel cloud-enabled geo-location aware QoS-centric spectrum allocation algorithm that is dynamically prioritizing the channels in accordance with the traffic demand, channel quality, and interference conditions. The second contribution is presenting an end-to-end methodology that is combining the spectrum sensing, and policy-controlled spectrum access within an unified architecture.

Literature Survey

The expansion of the wireless communication systems is increasing the demand for an efficient spectrum utilization. CRN is addressing this challenge by allowing secondary users in opportunistically access unused spectrum without interfering with the primary users.
Safi et al. [15] is examining the opportunistic spectrum sharing in the next-generation wireless systems using the Cloud Radio Access Network (C-RAN) architecture. Similarly, Iyer et al. [17] and Patil et al. [18] is investigating the dynamic resource assignment methods for opportunistic spectrum sharing in 6G networks. Farhat et al. [30] present an end-to-end overview of Cloud Radio Access Network architecture and it is analyzing the performance metrics in relation with the QoS and spectrum efficiency.
Zhang et al. [16] is proposing an intelligent spectrum sharing scheme, which is based on the radio maps for the Cloud-Based Satellite and Terrestrial Spectrum Shared Networks. Helmy et al. [19] is investigating the channel allocation strategies in LTE-based CRN. The study proposes a streaming algorithm that is prioritizing scalable video frames and ensures continuous playback under delay constraints. The algorithm is dynamically assigning the channels, which is based on the channel quality and buffer occupancy, which is improving the perceived video quality at the receiver side. Similarly, Hoobakht et al. [39] is introducing an optimization framework for the spectrum allocation in the Citizens Broadband Radio Service environment. Koliadenko et al. [38] is proposing a game-theoretic model for the frequency resource distribution that is guaranteeing the communication quality.
Kaur et al. [20] is introducing a cloud-assisted reinforcement learning scheme that optimizes resource allocation in the CRN. The framework aims to maximize energy efficiency while maintaining QoS constraints for a heterogeneous users. Tan et al. [35] is formulating the distributed spectrum access problem as the decentralized partially observable Markov decision process. Kumar et al. [27] and Kumar et al. [29] is exploring the deep reinforcement learning techniques for the resource allocation in the multi-tenant Cloud Radio Access Networks. Elhachmi et al. [41] further is extending the reinforcement learning techniques by developing a deep multi-user reinforcement learning for the CRN.
Benidris et al. [28] is proposing a distributed spectrum management approach for the cognitive Radio Internet of Things networks using the mobile edge computing technology. Liang et al. [26] is introducing an intelligent spectrum management framework that is combining the satellite and terrestrial networks using the Software Defined Networking and artificial intelligence. Sudhahar et al. [31] is proposing a Q-learning-based routing enhancement for the CRN using the modified Ad-hoc On-demand Distance Vector protocol. Similarly, Li et al. [40] is proposing a dynamic carrier allocation scheme for the internet-of-Vehicles systems in smart cities.
Jasim et al. [24] is examining the CR as a solution to spectrum scarcity by analyzing the underlay and interweave spectrum allocation methods. Fraz et al. [25] is proposing a Smart Sensing Enabled Dynamic Spectrum Management scheme that is combining the fuzzy controllers in optimizing the service response time and energy consumption. Ghafoor et al. [34] present a scheduling algorithm, which is based on the Orthogonal Frequency Division Multiplexing that minimizes cost while it is maintaining QoS requirements. Saravanan et al. [37] is introducing a Connected Resource Map induced Resource Allocation Scheme that is allowing the fair resource distribution among the secondary users. Barkire et al. [36] further is analyzing

the trade-offs in dynamic spectrum sharing for the 6G secondary users, which is showing the need for the efficient radio resource management techniques.

Analytical modeling also plays a significant role in evaluating spectrum management strategies. Louvros et al. [22] is proposing a two-stage queue model that estimates expected delays in cloud-based 5G and 6G networks. Tanveer et al. [43] is introducing a Continuous Time Markov Chain model in evaluating the connection availability in the CRN. Thakur et al. [21] is examining the hybrid spectrum access frameworks that is improving the spectrum utilization and energy efficiency in distributed architectures. Meanwhile, Khasawneh et al. [32] and Ahamad et al. [33] is reviewing the combination of the CR with the IoT systems and is proposing adaptive frameworks using the neural networks for the monitoring spectrum usage.

Table 1: Comparative Analysis on Related Works

Ref	Method	Algorithm	Metrics	Results	Limitation
[15]	Cloud-enabled CRAN spectrum sharing	Joint sensing-resource allocation	Throughput, QoS	Improved SU throughput	High computational complexity
[16]	Radio map based sharing	J-NPAP	Blocking rate, waiting probability	Reduced blocking rate	Limited scalability
[17]	Opportunistic spectrum sharing	Dynamic Resource Assignment	Throughput, QoS	Improved spectrum usage	Sensing overhead
[18]	Cooperative sensing with CRAN	DRA	Throughput, QoS	Enhanced SU performance	Delay in sensing
[19]	LTE-based CRN streaming	QoS-aware streaming algorithm	Delay, video quality	Stable playback	Application-specific
[20]	RL-based allocation	Cooperative RL	Energy efficiency, QoS	Reduced power usage	Training complexity
[21]	Hybrid spectrum access	SMC-MAC	Spectrum efficiency	Better utilization	MAC overhead
[22]	Queue model	Two-stage queue model	Delay	Accurate delay prediction	Simplified assumptions
[23]	Cloud Wi-Fi channel assignment	MDU-CACS	Channel quality	Improved network performance	Limited to Wi-Fi
[24]	Cloud CR spectrum allocation	Underlay/interweave methods	Throughput, queue time	Improved utilization	Limited adaptability
[25]	Smart sensing scheme	SSDSM	Response time, energy	Reduced energy consumption	Centralized control
[26]	SDN-based spectrum management	AI-based allocation	Utilization	Improved resource optimization	Deployment complexity
[27]	DRL-based resource allocation	DFQL	Throughput	Improved performance	Training overhead
[28]	MEC-based CRIoT	Distributed allocation	Latency, energy	Balanced performance	Limited scalability
[29]	DRL-based C-RAN allocation	Deep RL	Throughput	Better system utilization	High computational cost
[30]	CRAN architecture analysis	Analytical models	QoS	Improved spectral efficiency	Conceptual focus

[31]	Q-learning routing	Modified AODV	Delay, throughput	Improved routing efficiency	Limited network scale
[32]	CR-IoT review	Survey	Performance metrics	Comprehensive analysis	No implementation
[33]	Neural network framework	INN	Spectrum utilization	Improved monitoring	Limited experimentation
[34]	Scheduling framework	OFDM scheduling	QoS cost	Reduced cost	Complex optimization
[35]	Multi-agent RL	Deep recurrent RL	Throughput	Cooperative strategy learned	Training complexity
[36]	Dynamic spectrum sharing	Resource management schemes	Spectrum efficiency	Identified trade-offs	Limited evaluation
[37]	CRM-RAS allocation	Fairness scheduling	Latency, fairness	Improved QoS	Limited adaptability
[38]	Game-theoretic allocation	Frequency distribution model	Signal reception	Improved reliability	High complexity
[39]	Deterministic optimization	MILP	QoS	Optimal channel allocation	Computational cost
[40]	IoV resource allocation	Predictive allocation	QoS	Improved carrier allocation	Mobility uncertainty
[41]	Deep multi-user RL	Multi-agent Q-learning	Spectrum usage	Increased channel utilization	Training overhead
[42]	6G CRN technologies	Conceptual framework	Network capacity	Identified enabling tech	No algorithm
[43]	CTMC evaluation	Markov modeling	Connection availability	Accurate reliability modeling	Analytical only

Proposed Method

The proposed framework is introducing a cloud-enabled geo-location based QoS-centric spectrum and the channel allocation mechanism for the CRNs as in figure 1.

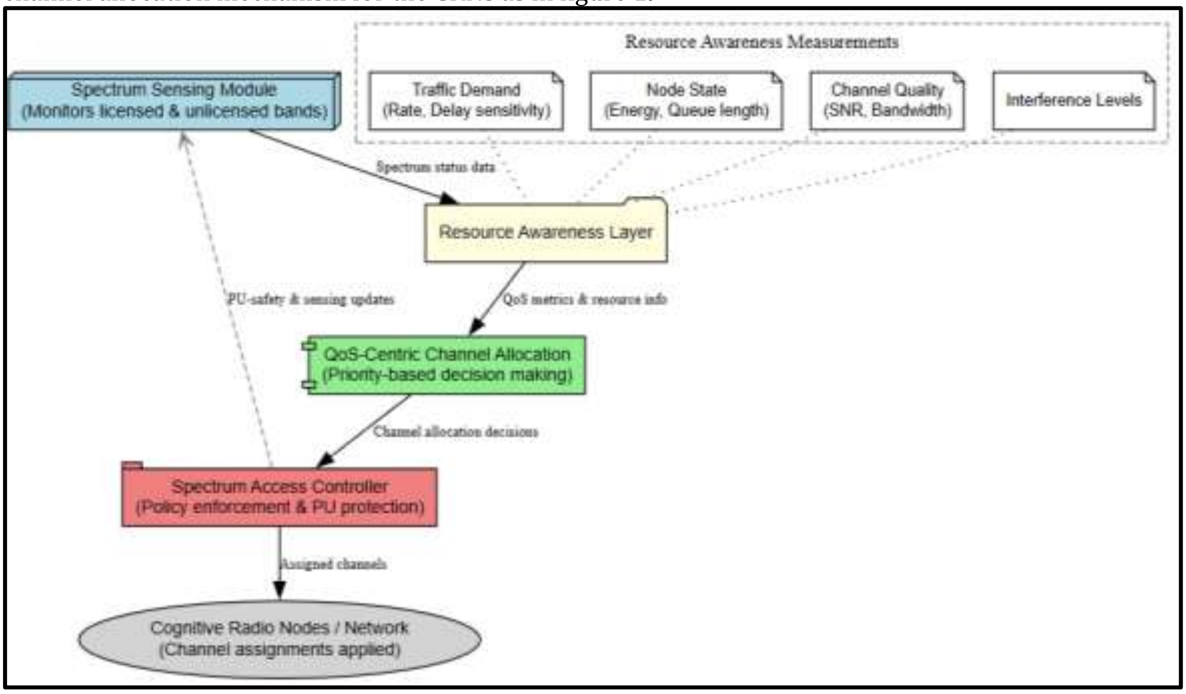

Figure 1: Proposed cloud-enabled geo-location based QoS-centric spectrum and channel allocation mechanism for Cognitive Radio Networks (CRNs).

Algorithm: Cloud-Enabled Geo-Location QoS Adaptive Spectrum Allocation (CGQ-ASA)

Input:

Spectrum availability map, user location data, QoS priority levels, channel state information

Output:

Optimal channel allocation for secondary users while maintaining QoS for primary users

Steps

1. Initialize cloud controller and register all cognitive radio nodes
2. Collect geolocation information from each node using GPS modules
3. Upload sensed spectrum availability data to the cloud database
4. Generate a dynamic geo-spectrum map representing channel availability and interference levels
5. Classify users into priority classes based on QoS requirements
6. Estimate channel quality indicators for each available spectrum band
7. Compute interference probability using geo-distance between transmitters
8. Assign priority weights to channels based on QoS demand and interference risk
9. Apply adaptive channel selection that maximizes weighted spectrum utility
10. Allocate channels to secondary users while ensuring protection threshold for primary users
11. Continuously monitor spectrum usage and update allocation decisions dynamically
12. If channel conflict occurs, trigger cloud-based reallocation procedure
13. Repeat allocation cycle periodically to adapt to network dynamics

Spectrum Sensing and Channel Availability Detection

The operation begins with the spectrum sensing process that is monitoring the licensed and unlicensed frequency bands. Each of the CR node continuously is observing the radio environment and it measures the signal energy within each of the channel. The sensing mechanism is identifying the presence of primary users in evaluating the received signal power level and then comparing it with the predefined detection threshold. If the signal power is exceeding the threshold, where the channel is remaining occupied by a primary user; otherwise, the channel is becoming available for the opportunistic access by the secondary users.

The received signal at a sensing node can be represented as

$$r_i(t) = \{n_i(t), H_0\ s_i(t) + n_i(t), H_1$$

where $r_i(t)$is the received signal at node i, $n_i(t)$is the noise component, and $s_i(t)$is the primary user signal. Hypothesis $H_0$is the channel is remaining idle, while hypothesis $H_1$is the presence of a primary user. The energy detection statistic for the sensing interval T is calculated as

$$E_i = \frac{1}{T}\int_0^T |\, r_i(t)\, |^2\ dt$$

The sensing decision follows

$$D_i = \{1, E_i > \lambda\ 0, E_i \leq \lambda$$

where λ is the sensing threshold. A value of $D_i = 1$ is that the channel is remaining occupied, whereas $D_i = 0$ is the channel availability.

The sensing results collected from all CR nodes form a channel availability matrix. A representation appears in Table 2, which is describing the status of monitored channels.

Table 2: Spectrum sensing results showing channel availability

Node	Channel 1	Channel 2	Channel 3	Channel 4
CR1	Idle	Busy	Idle	Idle
CR2	Busy	Busy	Idle	Idle
CR3	Idle	Idle	Busy	Idle
CR4	Idle	Idle	Idle	Busy

The sensing results are transmitted to the cloud server, which is aggregating the information to obtain a global view of channel availability. The centralized analysis is improving the sensing accuracy because the multiple nodes contribute to the detection process.

Geo-Location Mapping and Spatial Interference Analysis

After obtaining the sensing information, the system gathers geo-location coordinates from each of the CR node. Each of the node determines its geographic position using the positioning module and transmits the

coordinates to the cloud infrastructure. The location information allows the system to is analysing the spatial relationships between nodes and evaluate the potential interference between transmitters.
Let the location of node i be represented as

$$L_i = (x_i, y_i)$$

The Euclidean distance between the nodes $i$and $j$is calculated as

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

Interference between the nodes is reducing as distance is increasing. The interference power is generated by node i at node j is modeled using the path loss equation

$$P_{ij} = P_i(\frac{d_0}{d_{ij}})^\alpha$$

where P_i is the transmission power of node i, $d_0$is the reference distance, and $\alpha$is the path loss exponent. A geo-location dataset appears in Table 3.

Table 3: Geo-location information of cognitive radio nodes

Node	X Coordinate	Y Coordinate	Distance to PU (m)
CR1	12	18	320
CR2	25	14	280
CR3	33	27	400
CR4	19	30	350

The cloud infrastructure combines this information with the sensing results to determine which channels are remaining safe for each of the node, which is based on the geographic location.

Resource Awareness and Network State Monitoring

The next stage is involving a resource awareness analysis. The cloud platform is collecting the several network parameters that is influencing the spectrum allocation decisions. These parameters is including the traffic demand, queue length, node energy level, channel bandwidth, signal-to-noise ratio, and interference intensity.
The signal-to-noise ratio of channel k at the node i is calculated as

$$SNR_{i,k} = \frac{P_{i,k}}{N_0 B_k}$$

where $P_{i,k}$is the received signal power, $N_0$is the noise spectral density, and $B_k$is channel bandwidth.
The achievable channel capacity is following the Shannon's theorem

$$C_{i,k} = B_k log_2(1 + SNR_{i,k})$$

Traffic demand of the node i is represented as

$$T_i = \frac{D_i}{\Delta t}$$

where $D_i$is the required data volume and $\Delta t$is the service time.
The system is combining the parameters in forming a resource awareness matrix that is describing the operational condition of the network. A dataset appears in Table 4.

Table 4: Resource awareness parameters

Node	SNR (dB)	Bandwidth (MHz)	Queue Length	Energy Level
CR1	18	5	12	0.80
CR2	20	6	9	0.76
CR3	16	4	15	0.83
CR4	22	7	7	0.79

The cloud platform is processing these parameters in determining the suitability of each of the channel for the different communication tasks.

QoS Evaluation and Priority Score Calculation

The system then is evaluating the QoS requirement for each of the communication session. QoS requirements is including data rate, delay tolerance, reliability level, and packet loss tolerance.
The QoS score for the node i using the channel $k$is calculated as

$$Q_{i,k} = w_1 \frac{C_{i,k}}{C_{max}} + w_2 \frac{SNR_{i,k}}{SNR_{max}} + w_3(1 - I_{i,k}) + w_4 P_i$$

where
$C_{i,k}$is channel capacity

$SNR_{i,k}$ is signal quality
$I_{i,k}$ is interference level
P_i is application priority
w_1, w_2, w_3, w_4 represent weighting factors
The weights satisfy

$$w_1 + w_2 + w_3 + w_4 = 1$$

Channels with the higher QoS scores are becoming preferable for the allocation. A QoS score matrix appears in Table 5.

Table 5: QoS priority scores for channel allocation

Node	Channel 1	Channel 2	Channel 3
CR1	0.81	0.72	0.76
CR2	0.78	0.74	0.82
CR3	0.75	0.79	0.70
CR4	0.88	0.80	0.83

Channel Allocation Optimization

The allocation mechanism is selecting channels that tend to maximize the overall network utility while it is avoiding the interference with the primary users. The optimization objective is becoming

$$max \sum_{i=1}^{N} \sum_{k=1}^{K} x_{i,k} \, Q_{i,k}$$

subject to

$$\sum_{k=1}^{K} x_{i,k} \leq 1$$

$$x_{i,k} \in \{0,1\}$$

where $x_{i,k}$ is the allocation decision for the node i on channel k.
A channel assignment outcome is appearing in the Table **6**.

Table 6: Final channel allocation

Node	Allocated Channel	QoS Score
CR1	Channel 1	0.81
CR2	Channel 3	0.82
CR3	Channel 2	0.79
CR4	Channel 1	0.88

Spectrum Access Control and Policy Enforcement

After determining the allocation plan, where the spectrum access controller is verifying the regulatory constraints. The system is allowing the that no allocated channel overlaps with the active primary user transmission. If the system is detecting the primary user activity, where the controller is triggering a reassignment procedure.
The probability of interference with the primary users is estimated as

$$P_{int} = Pr(E_i > \lambda \mid H_1)$$

The system is maintaining the interference probability below a predefined threshold.

Feedback Monitoring and Dynamic Adaptation

Finally, where the system is performing continuous monitoring of communication performance. Each of the node periodically is reporting the transmission statistics such as throughput, packet delay, and the channel reliability.
Network throughput is hence calculated as

$$Throughput = \frac{\sum_{i=1}^{N} D_i}{T}$$

Average packet delay is hence calculated as

$$Delay = \frac{1}{N} \sum_{i=1}^{N} (t_{rx} - t_{tx})$$

The cloud controller updates QoS scores and the channel priorities, which is based on the performance measurements. This adaptive feedback mechanism is allowing that the network continuously is improving the allocation efficiency and it is maintaining high QoS.

To address all these security concerns, the proposed framework uses a security enforcement layer that is distributed across all four cooperative modules in the system. The spectrum sensing module uses cooperative spectrum sensing with reputation-based trust management to minimize the effect of faulty or malicious spectrum sensing nodes that could send false reports of channel availability. Within the cloud platform, the resource awareness layer uses encrypted communication channels and block chain-inspired ledger-based mechanisms to ensure that the QoS-centric channel allocation mechanism is provided with accurate node state information and traffic demand data that is not subject to any form of interference or malicious behaviour. The policy-controlled spectrum access controller uses an authentication and authorization gateway that authenticates all secondary users prior to channel access. It also continuously monitors for any unusual behaviour that could be indicative of spectrum misuse or primary user emulation attacks.

5. Results and Discussion

The evaluation is comparing the proposed method with the conventional methods such as Cloud-enabled CRAN spectrum sharing [15], Queue model [22], Q-learning [31], Game-theoretic allocation [38], and Deep multi-user reinforcement learning [41].

5.1 Experimental Settings

The experimental environment is using a simulation-based implementation that is modelling a cloud-assisted CR network which is including the multiple secondary users, primary users, and dynamic spectrum channels. The simulation environment is using the Python programming platform and it is getting executed on a workstation that contains an Intel Core i7 processor, 16 GB RAM, and Ubuntu Linux operating system.

5.2 Dataset Description

The dataset is realistic CR environments where channel availability fluctuates in accordance with the primary user activity. These measurements is providing the information regarding the frequency utilization, the signal strength, and the temporal spectrum availability.

Table 1: Spectrum Occupancy Dataset Description

Dataset Name	Frequency Band	Number of Samples	Access Link
RadioML Spectrum Dataset	400–2500 MHz	120,000 samples	https://www.deepsig.ai/datasets

5.3 Experimental Setup and Parameters

The CR simulation environment is containing several configurable parameters which is representing the network topology, spectrum characteristics, and reinforcement learning training variables.

Table 2: Simulation Parameters

Parameter	Description	Value
Number of Secondary Users	Active cognitive radio users	50
Number of Primary Users	Licensed spectrum users	15
Total Spectrum Channels	Available channels in the network	30
Channel Bandwidth	Bandwidth per channel	5 MHz
Simulation Area	Geographical coverage	1000 m × 1000 m
Transmission Power	Secondary user transmit power	0.1 W
Cloud Processing Interval	Allocation decision update interval	1 s
Learning Rate	Reinforcement learning training rate	0.001
Discount Factor	Future reward discount coefficient	0.9
Training Episodes	Number of training iterations	500

The experiment configures the CR nodes that operate under dynamic spectrum access conditions. Each of the node is performing a periodic spectrum sensing which is generating the channel occupancy observations. The observations are transmitted to the cloud controller which is performing centralized decision making. The reinforcement learning framework is containing a reward structure that is evaluating allocation efficiency. The reward function is increasing when the allocation achieves higher throughput and QoS satisfaction while it is maintaining minimal interference with the primary users.

The reward function $R_t$at time t is calculated as

$$R_t = \alpha U_t + \beta Q_t - \gamma I_t$$

Where $U_t$is spectrum utilization efficiency, $Q_t$is QoS satisfaction level, $I_t$is interference penalty, α, β, γrepresent weighting coefficients

The spectrum utilization efficiency is calculated as

$$U_t = \frac{\sum_{i=1}^{N} B_i^{all}}{\sum_{i=1}^{N} B_i^{av}}$$

Where B_i^{all} is the bandwidth that the system has allocated for the user i, and B_i^{av} is the total bandwidth which the system is detecting the as available in the environment.

The QoS satisfaction level is evaluating the successful service delivery ratio

$$Q_t = \frac{1}{N} \sum_{i=1}^{N} \delta_i$$

Where $\delta_i = \{1\ if\ QoS\ requirement\ satisfied\ 0\ otherwise$

The interference component is measuring the probability that the allocation is overlapping with the active primary user channel:

$$I_t = \frac{\sum_{j=1}^{M} C_j^{col}}{M}$$

where C_j^{col} is a collision event between the secondary user and the primary user.

5.4 Performance Metrics

The experimental evaluation is analyzing several quantitative metrics which is showing the performance of spectrum allocation algorithms in the CRN.

1. Spectrum Utilization Efficiency

Spectrum utilization is measuring how effectively the available radio spectrum resources is utilized by the secondary users.

$$SUE = \frac{B_u}{B_{tot}} \times 100$$

where $B_u$is the utilized spectrum bandwidth and $B_{tot}$is the total available spectrum bandwidth.

2. QoS Satisfaction Ratio

The QoS satisfaction ratio is evaluating the proportion of user requests which successfully is receiving the required service quality.

$$QoS_{ratio} = \frac{N_{sat}}{N_{tot}}$$

where $N_{sat}$is the number of user requests which is achieving the required throughput and latency constraints.

3. Average Allocation Latency

The allocation latency is measuring the time that the system requires in determining an appropriate spectrum channel for the secondary user request.

$$Lat = \frac{\sum_{i=1}^{N} T_i}{N}$$

where $T_i$is the allocation delay for each of the user request.

4. Throughput Efficiency

Throughput efficiency is measuring the successful data transmission rate within the CR network.

$$Throughput = \sum_{i=1}^{N} R_i$$

where $R_i$is the achieved data transmission rate for the user i.

5.5 Comparative Performance Evaluation over Training Episodes

This subsection is evaluating the performance of the proposed CGQSA framework in comparison with the several representative spectrum management approaches.

The evaluation is analyzing how the learning process is evolving as the number of training episodes is increasing. The simulation runs for the 500 training episodes, where each of the episode is a dynamic spectrum allocation cycle that is including the spectrum sensing, QoS evaluation, channel prioritization, and allocation optimization.

Spectrum Utilization Efficiency

Spectrum utilization efficiency is measuring the proportion of available spectrum bandwidth that the system successfully is assigning the to secondary users without causing interference to primary users.

Higher utilization is the that the allocation algorithm effectively is identifying idle channels and distributes them across the network.

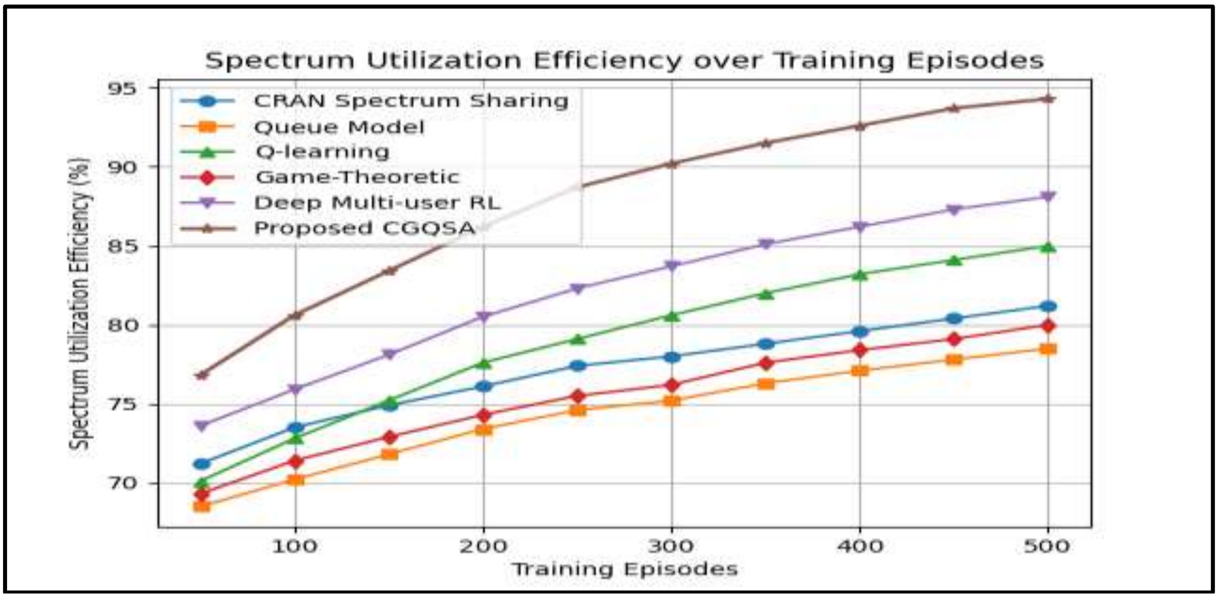

Figure 2: Spectrum Utilization Efficiency (%) over Training Episodes

The proposed framework consistently achieves the highest spectrum utilization because the cloud-based sensing aggregation is improving the detection accuracy of idle channels.

QoS Satisfaction Ratio

The QoS satisfaction ratio is the proportion of communication sessions that successfully meet the required data rate, latency, and reliability constraints. The metric is evaluating how effectively the allocation mechanism supports service quality for the diverse application demands.

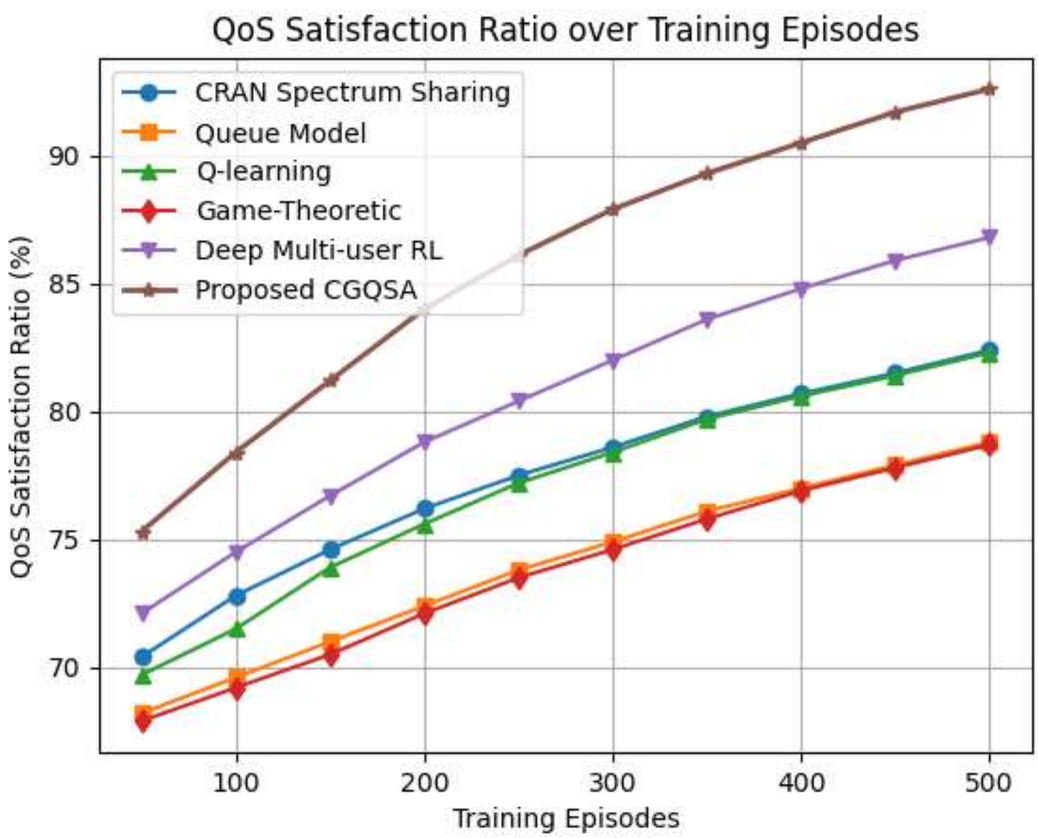

Figure 3: QoS Satisfaction Ratio (%) over Training Episodes

The QoS performance is improving the gradually because the proposed system is dynamically prioritizing channels in accordance with the service requirements and the channel conditions.

Average Allocation Latency

Allocation latency is measuring the time that the system requires in determining a channel assignment decision after receiving a user request. Lower latency is the faster decision processing and more efficient cloud resource coordination.

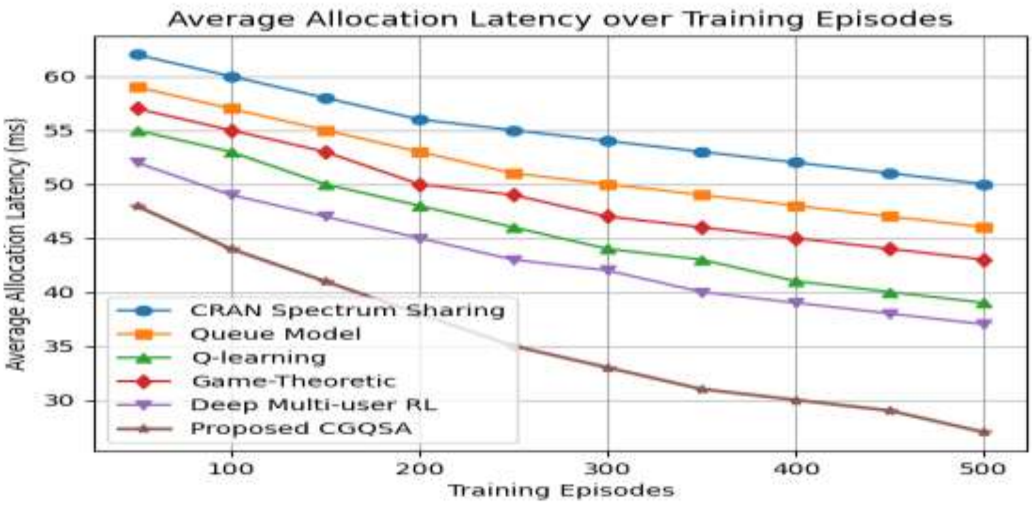

Figure 4: Average Allocation Latency (ms) over Training Episodes

The reduction in latency occurs because the proposed architecture is using a centralized cloud controller that is maintaining a global network state and quickly is performing allocation decisions.

Network Throughput Efficiency

Throughput efficiency is evaluating the total data successfully transmitted across the network during the simulation period.

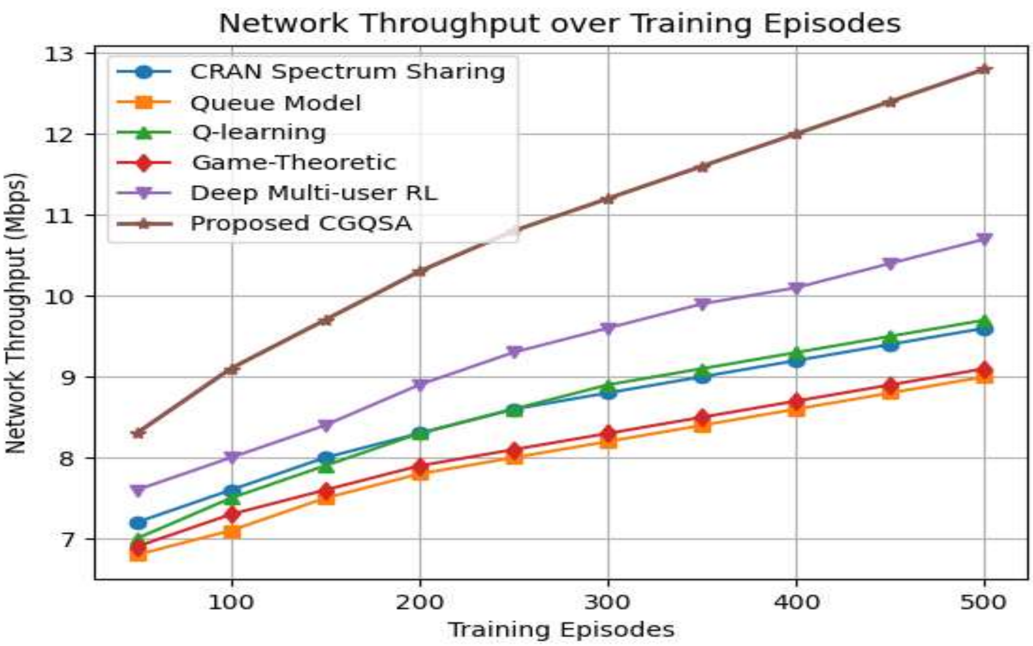

Figure 5: Network Throughput (Mbps) over Training Episodes

The throughput performance is increasing significantly because the proposed algorithm effectively balances channel quality, QoS demand, and the interference avoidance during the channel selection.

Conclusion

The study is presenting a cloud-enabled geo-location based QoS-centric spectrum allocation framework for the CRN which is addressing the challenges that arise from the dynamic spectrum access and heterogeneous user demands. The proposed architecture is combining a cloud controller with the reinforcement learning allocation mechanism that is analyzing the global spectrum sensing information and the QoS requirements of the secondary users. The cloud platform is maintaining a centralized spectrum knowledge base which is allowing the system to perform efficient channel selection and allocation decisions. The reinforcement learning module gradually is improving the allocation policy through the repeated interaction with the wireless environment, which is allowing the system to adapt to the fluctuating spectrum availability that primary users cause. The results are showing that the proposed method is achieving a spectrum utilization efficiency of 94.3%, which is the effective exploitation of the available spectrum resources. The QoS satisfaction ratio has reached 92.6%, which is confirming that the system successfully is supporting the service quality requirements of the users. The network throughput has increased to 12.8 Mbps, which is showing the improved communication efficiency of the CR network. The future direction of this work will be centered around the creation of lightweight cryptographic protocols that are appropriate for resource-constrained devices used in cognitive radio, as well as investigating the potential of federated learning for enhancing security while maintaining privacy. In all, this work presents a holistic architecture that not only optimizes spectrum efficiency but also satisfies the fundamental security requirements for the successful deployment of next-generation wireless networks.

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