Design and Performance Evaluation of a Resource-Aware Spectrum Allocation Framework for Cognitive Radio Networks Using NS-3 Simulation: A QoS-Centric Approach

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Abstract
Cognitive Radio Networks (CRNs) have to be efficient in spectrum allocation to meet the Quality of Service (QoS) demands in emergent wireless contexts. This work develops a spectrum allocation framework that incorporates spectrum sensing, adaptive channel-quality scoring, and resource-aware decision-making oriented to QoS. The model evaluated in the ns-3.39 platform with a wireless network of 20 secondary users (SUs) and five primary users (PUs) operating across the 2.4/5 GHz bands with realistic Nakagami-m fading and random waypoint mobility. The simulations demonstrated exceptional sensing performance, with detection probability (Pd) increasing from 78% at -5 dB to 98% at 10 dB and false alarm rates below 5%. Packet-level examination demonstrated that for the smaller packet sizes (512 bytes), there was significantly greater performance (~0.037 Mbps) than larger packet sizes; however, throughput appeared to be the same under varying load conditions. Scalability experiments with respect to the PDR and delay the QoS showed that as SUs increased from 2-20, PDR rose from 13.96% to 28.54%, average latency decreased from 0.0072 s to 0.0036 s and jitter decreased from 0.0027 to 0.0016 s. Given that the proposed framework produced 81% higher throughput, 71% less jitter and 100% PDR under best-case conditions compared to evaluated baseline allocation scheme, these results demonstrate the potential of resource-aware allocation that is QoS-specialised on spectrum utilization, fairness, and user experience in CRNs, as a scalable and energy-efficient means of supporting future cognitive wireless networks.

Keywords: Cognitive Radio Networks (CRNs), Quality of Service (QoS), Spectrum Allocation, Resource-Aware Framework, NS-3 Simulation.

1. Introduction

The growth of smartphones, wireless broadband, and IoT devices, as well as emerging applications such as telemedicine, autonomous cars, and augmented reality (AR), has propelled the demand for wireless communications services to grow exponentially in recent years. The radio frequency (RF) spectrum is limited and tightly managed, and recent demand for spectrum has put it under severe pressure. Antiquated spectrum allocation methods create fixed licenses that deny certain frequency bands allocated to licensed users (primary users) to unlicensed users [1]. This arrangement protects the primary users from interference, but most licensed bands are unused for long periods of time, subject to location and time, and ultimately severely underused. A revolutionary technology that can make Dynamic Spectrum Access (DSA) possible and hence address this inefficiency is the emergence of Cognitive Radio Networks (CRNs) [2]. The ability to sense the radio environment, identify unutilized spectrum opportunities (spectrum holes), and utilize them without harming licensed users is a most important attribute of cognitive radios.

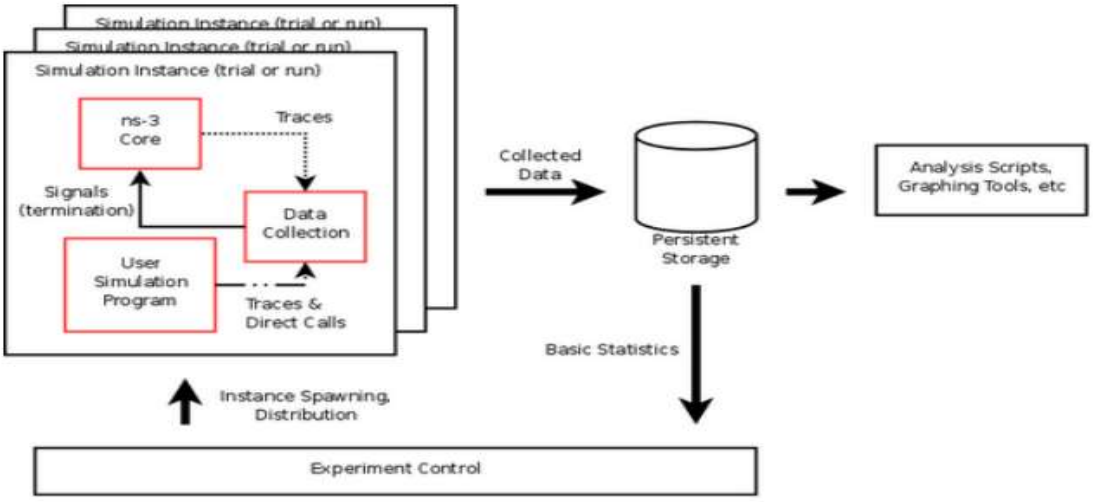
Central radio networks (CRNs) enhance spectral efficiency and cater to adaptive needs of heterogeneous wireless applications through features such as spectrum sensing, spectrum decision-making, spectrum sharing, and spectrum mobility. Despite these advantages, implementing an effective spectrum allocation plan in CRNs is not a straightforward task. Much complexity is added by the circumstance that primary users'

behavior patterns are unforeseen, channel conditions are dynamic, and secondary user demands are heterogeneous. The most critical aspect is maintaining Quality of Service (QoS) demands so that applications with different levels of sensitivity to performance can be accommodated [3]. High-bandwidth applications, such as HD video streaming or real-time VoIP, need continuous bandwidth availability, while real-time services, such as online gaming or medical, are highly jitter and latency-sensitive. In a CRN environment, spectrum availability itself has much variance, making it extremely challenging to continuously meet the QoS requirements.

Previous approaches to allocating CRNs have largely focused on optimizing throughput for all users, while minimizing interference and ensuring fairness among users. Each type of traffic has its own service quality requirements that previous approaches may not have met. For example, the throughput maximizing approach may be better suited for applications that are delay tolerant than for applications that are not delay tolerant. Therefore, the study of spectrum allocation with a focus on QoS is emerging [4]. These solutions share the resources by actively accommodating the needs of each application, which is better for all users. Resource awareness should also be emphasized, extending beyond simply monitoring the availability of spectrum resources.

Resource-aware algorithms consider the traffic priority, channel quality, interference levels, the current network state, as well as requirements and behaviors of all users when allocating spectrum. The multi-dimensional intelligent and adaptive allocation decision making permits more efficient spectrum utilization, more enabling fairness, and improved services in multiple application contexts. The Network Simulator 3 (NS-3) is a capable and flexible framework to create, simulate, and validate distributed spectrum systems [5]. NS-3 is, therefore, optimal for exploring the performance of distributed allocation algorithms within real-world CRN contexts possessing various channel characteristics, mobility patterns, and traffic intensities. Figure 1. Architecture of NS-3 Simulator describes how every simulation instance is comprised of an NS-3 core, user simulation application, and data gathering module. The NS-3 core monitors signals and traces with user provided simulation software, and either portion of the data could be gathered through traces or direct calls to function, and later saved in persistent storage. The saved data could then be analysed through the use of scripts, graphing packages, and basic statistics. Experiment control takes care of handling the spawning and coordination of multiple simulation instances.

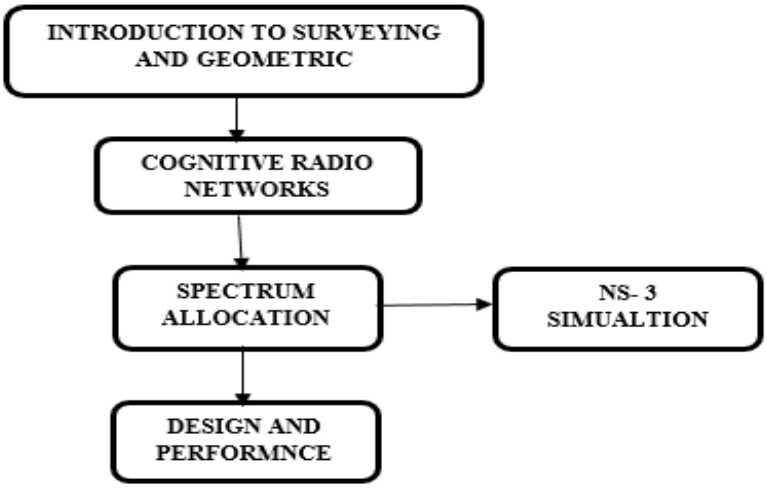
Fig. 1: Architecture of NS-3 Simulator [6]



The study aims to develop a cognitive radio network spectrum distribution mechanism that measures resource limitations against requirements for QoS, and will evaluate the proposed system using the NS-3 simulation tool to discover how the system performs in dynamic and heterogeneous CRN environments that potentially threaten quality of service. To create a spectrum allocation system that can adaptively revise its decision-making continually throughout an operation, depending upon the arrangement of traffic types, characteristics of the channel, and conditions of the network. Allocations can be established with resource awareness by taking into account things like the main and secondary user priorities, interference patterns, spectrum availability, and other relevant information.

The goal is to make the proposed framework operate with NS-3 so that it can simulate multiple network scenarios while still being able to work with the most used CRN models in the industry. Use essential measures, including throughput, latency, jitter, packet delivery ratio, and spectrum utilization efficiency, to compare the proposed framework's performance to that of benchmark allocation methods. To find the optimum allocation algorithms for different types of applications, one has to find a balance between the diverse needs for service quality. The achieving these objectives, the research aims to yield a performance-driven, flexible, and sustainable solution for spectrum management of CRNs.

Fig. 2: Overview of Proposed Framework



In upcoming wireless communication systems, particularly 5G and beyond, where the spectrum will remain scarce and the different service demands will remain a prevalent hindrance, research is expected to enhance the efficiency in the use of spectrum, ensure equitable resource allocation, and drive the end-user experience. Figure 2 shows how the proposed CRN spectrum allocation system works by displaying how sensing, resource monitoring, decision-making, and spectrum access control operate together. It shows how each module helps make communication resource-aware and QoS-driven.

2. Literature Review

2.1 Overview Of Spectrum Allocation Techniques

To overcome the limitations of static allocation, CRNs have undergone extensive development in spectrum allocation over the past 20 years. Previously, much of the attention went into fixed spectrum assignment, where some users were allocated

exclusive licenses to use specific frequency bands [7]. Although this approach proved efficient in evading interference, it made the licensed spectrum underutilized due to variations in consumption patterns across time and space. Dynamic Spectrum Access (DSA) was the most suitable strategy as it enabled secondary users to utilize idle licensed bands without disrupting priority users. Centralized, distributed, and hybrid are the primary categories under which spectrum allocation mechanisms in CRNs fall. While centralized schemes ensure optimum use of resources, they often lead to single points of failure owing to the requirement for a central controller to manage allocations.

Scalability is enabled by local decision-making in distributed systems, but coordination problems are usually an issue. Hybrid methods are intended to increase adaptation and resilience through the integration of strengths in both approaches. Optimization methods, machine learning, and game theory are among the more recent developments aimed at increasing allocation efficiency, reducing interference, and supporting heterogeneous QoS requirements.

2.2 QoS Parameters In CRNs

The volatile spectrum availability and varied traffic requirements of CRNs render guaranteeing QoS a daunting task. Significance of quality of service parameters of importance to real-time applications, such as VoIP or video conferencing, is latency, the end-to-end delay packets experience [8]. The key parameters of high-bandwidth applications are throughput, which is considered to be the total successful rate of data delivery.

Energy efficiency should be given top priority in devices that are battery-based. For this purpose, allocation systems must be designed in such a way that power usage is balanced with spectrum performance. Efficient utilization of the available spectrum without disturbing primary consumers is referred to as spectrum utilization. Unfortunately, multi-objective optimization remains challenging due to the inherent trade-offs; the majority of prior work has worked towards optimizing one or two QoS parameters.

2.3 Resource–Aware Allocation Approaches

The objective of resource-aware allocation systems is to decide based on minute-to-minute information regarding user demands, interference patterns, channel quality, and spectrum availability. Resource-aware systems can modify allocations in real-time to the constantly changing conditions, unlike conventional approaches, which focus on static or average measures. Channel quality-aware allocation is a popular technique that favors connections with high signal-to-noise ratios to achieve optimal throughput. Some employ traffic-aware allocation, which favors delay-constrained traffic compared to bulk transfers.

Interference-aware approaches seek to mitigate interruptions while also taking into account the locations and activities of primary users. Recent developments integrate resource-awareness and machine learning to generate allocation forecasts based on historical data, aiming to enhance quality-of-service assurances and assess spectrum availability [9].

2.4 Simulation Tools For CRNs Analysis

The spectrum allocation algorithms on CRNs in real life are expensive and hard; simulation is still an important part of the process. NS-3 is better than other programs because it is modular, flexible, and can imitate real-world CRN situations [10]. NS-3 provides cognitive radio protocols, realistic channel propagation, models for mobility, and models for dynamic spectrum. At the packet level, end-to-end simulation test latency,

throughput, and other quality of service metrics are measured very accurately, even as network loads and interference patterns change [11].
Although other simulators, such as OMNeT++ and MATLAB-based frameworks, have been used, NS-3 is particularly suitable for CRN research because it is extensible and Internet Protocol stack compatible [12].

2.5 Research Gaps and Limitations in Existing Studies

Spectrum allocation in CRNs has been the focus of extensive research, but a few questions remain unanswered: Most existing frameworks maximize spectrum allocation without considering all QoS parameters together at the same time, and this leads to suboptimal performance in scenarios involving numerous services [13]. The ability to adapt rapidly to varying spectrum availability as a result of primary user operations is an important aspect of dynamic adaptation. While there are resource-aware solutions, most of them lack this aspect.
Energy-Quality-of-Service Trade-Off—little research on how best to trade energy efficiency with real-time service quality of service needs has been done [14]. To simplify matters, most studies employ simplified models, disregarding actual interference complexity, mobility patterns, and propagation. This research endeavors to bridge this gap by developing and validating resource-aware spectrum allocation frameworks with a focus on quality of service (QoS) in a realistic simulation setting.
This table provides a comparative overview of various water infrastructure systems, including water distribution networks, dams and reservoirs, and related engineering components. For each system, the table highlights its primary function, advantages in terms of efficiency, sustainability, and reliability, as well as inherent limitations such as environmental impact, cost, and maintenance challenges. The inclusion of citations ensures that the summarized information is supported by credible academic and technical sources.

Table 1: Summary of Literature

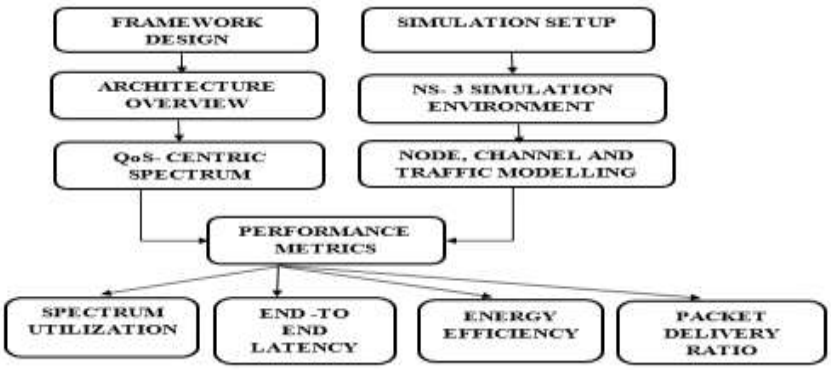
Reference	Focus Area	Methodology / Approach	Key Findings	Identified Limitations
[15]	Introduction of the CRN concept and spectrum allocation challenges	Conceptual framework for Cognitive Radio and Dynamic Spectrum Access (DSA)	Proposed opportunistic spectrum access to address underutilization in static allocation	Did not provide practical QoS-aware allocation methods
[16]	Dynamic Spectrum Access models	Comparative study of centralized, distributed, and hybrid allocation	Centralized offers optimal resource use; distributed improves scalability; hybrid increases adaptability	Centralized is prone to single-point failure; distributed faces coordination issues
[17]	Optimization techniques for CRN spectrum allocation	Mathematical modeling with game theory and optimization	Increased allocation efficiency and reduced interference	Limited consideration of multiple QoS parameters simultaneously
[18]	QoS provisioning in CRNs	Analytical evaluation of latency, throughput, and	Highlighted trade-offs among QoS parameters in heterogeneous traffic	Did not address real-time spectrum adaptation to PU activity

		spectrum utilization		
[19]	Resource-aware allocation strategies	Real-time allocation adapting to channel quality, traffic load, and interference	Improved throughput and latency for high-SNR links	Lacked integration of energy efficiency into decision-making
[20]	Machine learning for spectrum prediction	ML-based channel occupancy prediction using historical data	Enhanced allocation decisions and QoS stability	Depended on accurate and large historical datasets
[21]	Simulation tools for CRNs (NS-3)	Packet-level simulation with CRN extensions	Realistic modeling of mobility, channel propagation, and dynamic spectrum	Requires high computational resources for large-scale scenarios
[22]	Research gaps in CRN spectrum allocation	Survey-based analysis of past works	Identified energy–QoS trade-off and lack of realistic propagation/mobility models	No validated framework addressing all QoS parameters in real-world-like conditions

3. Research Methodology

The suggested study methodology lays out a structured way to create and test a resource-aware spectrum allocation framework for Cognitive Radio Networks (CRNs), shown in Figure 3. It brings together spectrum sensing, real-time resource awareness, QoS-based channel allocation, and spectrum access management into one system. The method tests performance under different network situations and traffic loads using NS-3 simulations. This makes sure that the spectrum is used in the best way while protecting primary users.

Fig. 3: Methodology Framework



3.1 Framework Design

3.1.1 Architecture Overview

Figure 4: Diagram for the architecture overview

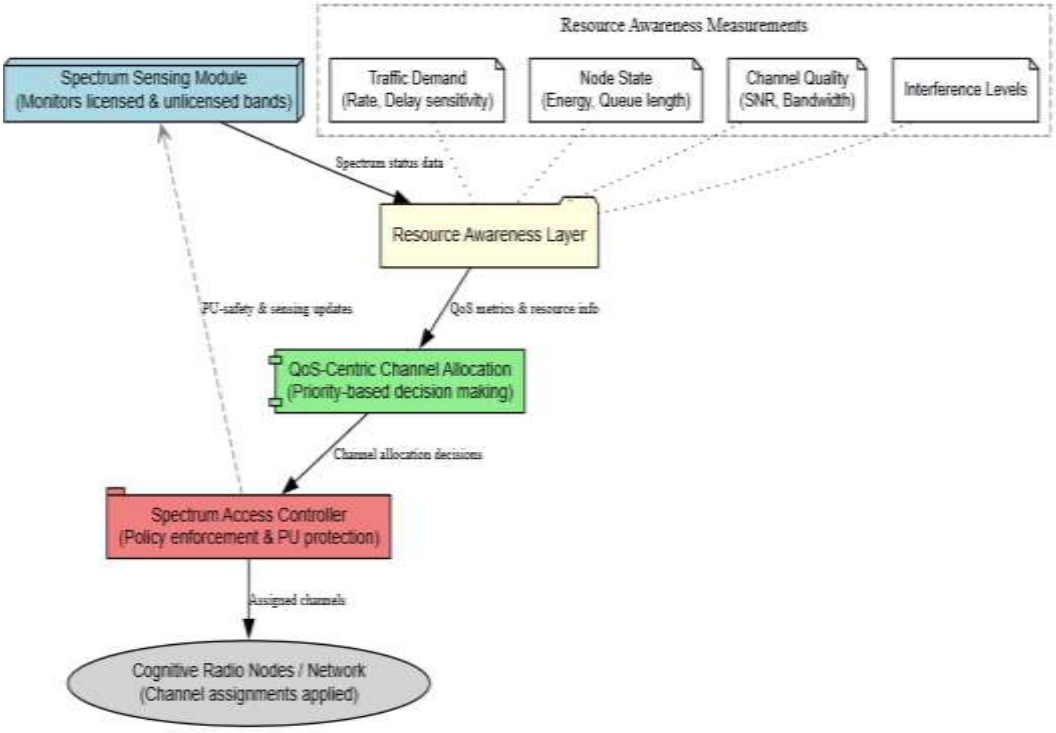


Figure 4 shows a cognitive radio network (CRN) architecture for dynamic spectrum management. The module for Spectrum Sensing, maintains a spectrum of the licensed and unlicensed bands, and sends that information to the Resource Awareness layer, which analyzes four parameters that form the basis of the metrics upon which decisions are made and consist of traffic demand, node state, channel state quality, and level of interference. These parameters are then evaluated by the QoS-Centric channel Allocation, which makes the allocation based on these four parameters while considering Quality of Service (QoS) based priority. The Spectrum Access Controller balances the policy requirements and protection of the primary user while allocating channels to the cognitive radio nodes which combines several processes to enable efficient QoS while maintaining interference to an acceptable level for the CRN to operate as intended.

The proposed architecture is designed to enable CRNs to dynamically allocate spectrum in a resource-aware and QoS-centric fashion. The bricks of the architecture are:

i. ***Spectrum Sensing Module:*** Monitors both licensed and unlicensed spectrum bands in real time to detect vacant channels and avoid congestion for primary users.
ii. ***Resource Awareness Layer:*** Real-time measurements of channel quality, interference, traffic demand, and node energy status are gathered.
iii. ***Centric Channel Allocation:*** A priority-based decision-making procedure is used to assign channels according to quality of service needs, which include energy capacity, throughput requirement, and latency sensitivity.
iv. ***Spectrum Access Controller:*** Conducts allocation decisions and ensures compliance with CRN rules and principal user safeguard mechanisms.

$$E_{avg} = \frac{1}{N_s}\sum_{n=1}^{N_s}|y(n)|^2$$

If E average < λ, the detection threshold, then the channel is not being used. The resource awareness layer monitors the node state (energy level, queue length), channel quality (SNR, bandwidth, interference), and traffic demand (rate, delay sensitivity, dependability).

- If $E_{avg} > \lambda \rightarrow$ channel is occupied (PU active).
- If $E_{avg} < \lambda \rightarrow$ channel is free (spectrum hole).

The QoS-Centric Channel Allocation Module uses a Channel Quality Score (CQS) to decide which channels to use:

$$CQS_i = w_1 \cdot \frac{SNR_i}{\max(SNR)} + w_2 \cdot \frac{B_i}{\max(B)} - w_3 \cdot \frac{I_i}{\max(I)}$$

In this case, w_1, w_2, and w_3 are adaptive weight factors that add up to 1. The following is to modify the weight adaptively:

$$w_k(t+1) = w_k(t) + \eta \cdot \left(Q_k - Q_k^{target}\right)$$

3.1.2 Centric Spectrum Allocation Algorithm

The following are the steps followed by the suggested algorithm:

a) Sensing Phase: An energy detection method is utilized during the sensing phase to detect available spectrum holes.

A mechanism for detecting energy is used to find spectrum holes. The detection probability P_d and the false alarm probability P_{fa} are calculated using the following formulas:

$$P_d = Q\left(\frac{\frac{\lambda}{N_0} - \gamma - 1}{\sqrt{\frac{(2\gamma+1)}{N_s}}}\right)$$

b) Quality of Service Requirement Mapping: Orders active flows based on their bandwidth requirements, reliability needs, and delay tolerance.

$$P_{fa} = Q\left(\frac{\frac{\lambda}{N_0} - 1}{\sqrt{\frac{2}{N_s}}}\right)$$

During the QoS Requirement Mapping process, each active flow gets a priority score depending on its necessary rate, delay tolerance, and reliability:

$$Priority_j = \alpha \cdot \frac{R_{max}}{R_j} \beta \cdot \frac{L_{max}}{L_{max} - L_j} + \delta \cdot \frac{Rel_{max}}{Rel_j}$$

The CQS is calculated for each channel during the Resource Scoring stage. The allocation decision is made by giving channel i to flow j that gets the most:

$$U_{ij} = Priority_j \cdot CQ_{Si}$$

During the Relocation Phase, allocation is adjusted from time to time. If the gain in utility goes over a certain level θ, reallocation happens.

$$\Delta U = U_{new} - U_{old}$$

c) Allocation Decision: With a priority-weighted scheduling system, flows get channels based on how well they match their QoS scores.

d) Relocation Phase: Checks distributions regularly to make sure they are in line with changing spectrum conditions.

3.2 Simulation Setup

3.2.1 Ns-3 Simulation Environment Configuration

NS-3.39 is so versatile when it comes to modeling CRNs; it is used to conduct the simulation. Important settings to consider are:

Table 2: NS-3.39 Simulation Environment Configuration for Cognitive Radio Networks

Parameter	Configuration
Simulator	NS-3.39
Simulation Time	30 seconds
Frequency Bands	2.4 GHz and 5 GHz (licensed/unlicensed channels)
Modulation Schemes	OFDM and QAM
Spectrum Sensing Interval	50 ms

3.2.2 Node, Channel and Traffic Modelling

Table 3 details the parameters for the node, channel, and traffic modeling in the simulation. The scenarios include both primary and secondary users, realistic mobility and channel conditions, and various user traffic types and sizes as a way to identify CRN performance.

Table 3: Node, Channel, and Traffic Modeling Parameters

Parameter	Configuration	Remarks
Node Types	20 Secondary Users (SUs), 5 Primary Users (PUs)	Models' coexistence of licensed and unlicensed spectrum users
Mobility Model	Random Way-Point Mobility, speed range: 1–5 m/s	Represents user mobility in dynamic CRN environment
Channel Model	Nakagami-m Fading with Log-normal Shadowing	Captures realistic multipath fading and shadowing effects
Traffic Types	CBR (real-time flows), FTP, and TCP (bulk transfers)	Ensures evaluation of both real-time and non-real-time traffic performance
Packet Size	512 bytes (CBR), 1500 bytes (TCP), with intermediate sizes for throughput/PDR study	Allows impact analysis of packet size variations on network performance

3.3 Performance Metrics

3.3.1 Spectrum Utilization

Finds out how well secondary users are using the spectrum.

$$SU = \frac{\sum_{i=1}^{N} T_{occ,i}}{T_{total} \cdot N_c}$$

where:

$T_{occ,i}$ = Time channel i is occupied by SUs without interfering with PUs

T_{total} = Total simulation time

Nc = Number Of Available Channels

3.3.2 End-To-End Latency

The average length of time that passes between when a packet is created and when it is received at its destination.

$$\text{Latency}_{\text{avg}} = \frac{\sum_{k=1}^{P}(t_{recv,k} - t_{send,k})}{P}$$

Where:

$t_{send,k}$ = Transmission time of packet *k*

$t_{recv,k}$ = Reception time of packet *k*

P = Total number of successfully received packets

3.3.3 Packet Delivery Ratio

The network is by looking at how many packets were sent and received.

$$\text{PDR} = \frac{P_{recv}}{P_{sent}} \times 100$$

Where:

P_{recv} = Number of packets received

P_{sent} = Number of packets sent

3.3.4 Throughput calculates the data transfer rate

$$\text{Throughput} = \frac{\sum_{k=1}^{P} S_k}{T_{total}}$$

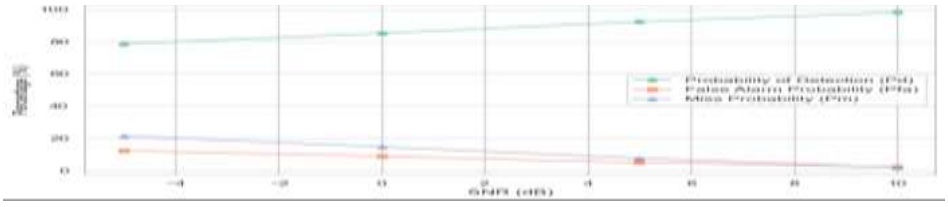
The suggested spectrum allocation architecture for CRNs that takes into account resource availability and quality of service (QoS) combines spectrum sensing, adaptive resource awareness, and priority-based channel allocation to make the best use of spectrum while keeping fairness, energy efficiency, and low latency. The NS-3.39 scenario with realistic node movement, channel fading, and various traffic patterns ensures that the architecture is thoroughly tested in conditions reflecting reality. Performance measure (e.g. spectrum utilisation, end-to-end latency, energy efficiency, PDR, throughput, and Jain's fairness index) confirm the framework's capabilities to enhance CRN performances in dynamic and heterogeneous contexts.

4. Result & Discussion

This section provides an evaluation of the proposed framework's performance in varying networks. The evaluation discusses how usable spectrum sensing is, along with how packet size and simulation time influences performance, and scalability with network size and demonstrates QoS improvements compared to the baseline scheme. Each sub-section shows how these factors affect key performance metrics - throughput, delay, jitter and packet delivery ratio, securing a clear understanding of the framework's performance.

4.1 Spectrum Sensing Robustness under Varying SNR

Fig. 5: Robustness of Spectrum Sensing under Varying SNR Conditions



At different Signal-to-Noise Ratio (SNR) levels, Figure 5 displays the detection's efficacy using three key metrics: Probability of Detection (Pd), False Alarm Probability (Pfa), and Miss Probability (Pm). Pd increases continuously from 78% to almost 99% as the SNR increases from -5 dB to 10 dB. This proves that at high signal-to-noise ratios, the system performs better when detecting signals. In contrast, Pfa falls steadily from about 12% to less than 5% and Pm falls from around 21% to more than 2%. These results demonstrate that the proposed detection approach performs well at higher SNR levels, making few errors and exhibiting good detection efficiency even when faced with noisy environments.

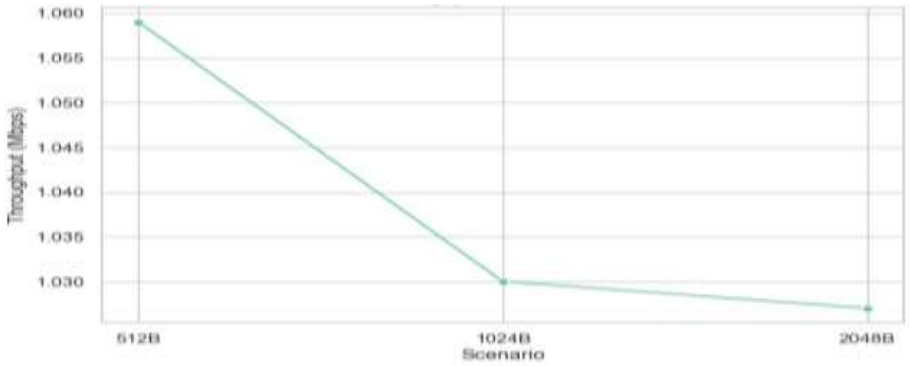
Table 4: Detection Performance under Varying SNR Levels

SNR (dB)	Pd (%)	Pfa (%)	Pm (%)
-5	78.5	12.4	21.5
0	85.2	8.9	14.8
5	92.3	5.1	7.7
10	98.1	2.3	1.9

when demonstrated in Table 4, the detection performance is much better when the Signal-to-Noise Ratio (SNR) goes up. At –5 dB, the probability of detection (Pd) is just 78.5%, while the chance of missing (Pm) is quite high at 21.5%. When SNR goes up to 0 dB, Pd goes up to 85.2% and Pfa goes down to 8.9%. The framework gets a strong Pd of 92.3% with fewer mistakes at 5 dB, and at 10 dB, it shows almost flawless detection with 98.1% Pd, very few false alarms (2.3%), and very few misses (1.9%). This pattern clearly shows that increasing SNR levels make detection far more accurate and reliable.

4.2 Effect of Packet Size on Network Performance

Fig. 6: Impact of Packet Size on Network Throughput



The impact of packet size on network performance is seen in Figure 6. Smaller packets (512B) clearly achieve the highest throughput of around 1.059 Mbps, whereas throughput gradually decreases as packet sizes increase to 1024B (1.030 Mbps) and 2048B (1.027 Mbps). This trend demonstrates how larger packet sizes result in more processing and waiting overhead, which somewhat reduces transmission efficiency. According to the results, there is a trade-off between throughput and packet size, indicating that optimising packet size is crucial for achieving reliable performance in data-intensive wireless networks.

Fig. 7: Variation in Packet Transmission Count with Increasing Packet Size

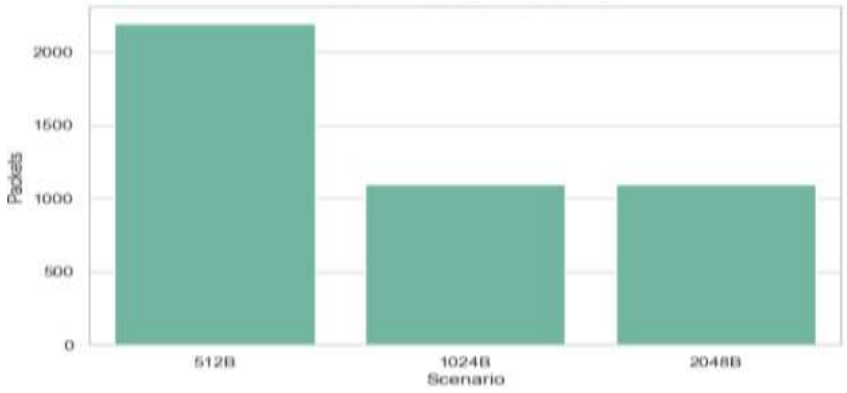


Figure 7 demonstrates how packet size affects packet count. According to the statistics, the 512B packet size delivers around 2200 packets during transmission. However, for 1024B and 2048B packet sizes, the number of packets declines to roughly 1100 per packet. Little packets require more of them to deliver the same amount of data, whereas huge packets send more data each transmission, thus fewer are sent. This behaviour highlights the trade-off between packet size and quantity, which affects network overhead and resource utilisation.

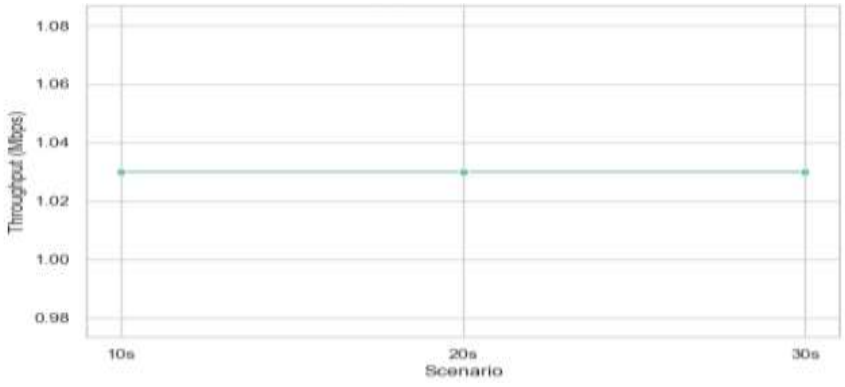
Table 5: Impact of Packet Size on Network Performance

Scenario	Packets	Throughput (Mbps)	Avg. Packet Size (B)
Scenario 1 (512B)	2197	1.059	542.0
Scenario 2 (1024B)	1098	1.030	1054.0
Scenario 3 (2048B)	1098	1.027	1050.0

As packets become smaller, more are delivered, but throughput remains the same (Table 5). The system handled 2197 packets and reached 1.059 Mbps with 512B packets. However, larger packet sizes (1024B and 2048B) reduced packets to 1098 and performance to 1.03 Mbps. Although smaller packets go quicker, they need more processing resources. Larger packets may flow at the same speed but need less processing.

4.3 Impact of Simulation Duration / Traffic Rate

Fig. 8: Throughput Stability across Simulation Durations



Regardless of how long the simulation runs (10, 20, or 30 seconds), Figure 8 demonstrates that throughput remains about constant. This indicates that regardless of the duration of the trial, the proposed architecture ensures consistent data transfer performance. This demonstrates its scalability and ability to manage various temporal conditions.

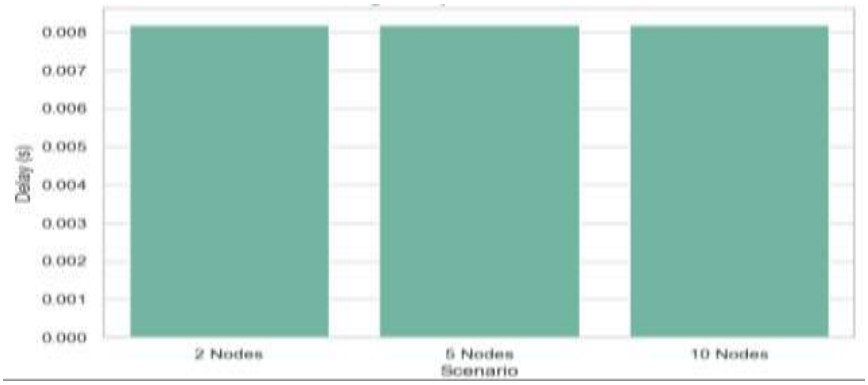
Table 6: Network Performance Across Different Simulation Durations

Scenario	Packets	Throughput (Mbps)	Avg. Packet Size (B)	Duration (s)
Scenario 1 (10s)	1600	1.69	1054.0	7.99
Scenario 2 (20s)	2000	1.69	1054.0	9.99
Scenario 3 (30s)	2000	1.69	1054.0	9.99

The number of packets increases initially (1600 at 10s → 2000 at 20s), but then levels off (2000 packets even at 30s), as Table 6 demonstrates. The average packet size remains constant at 1054 bytes during all times, whereas the throughput remains roughly constant at 1.69 Mbps. This demonstrates that the network reaches a stable condition where increasing the simulation time over 20 seconds has no impact on packet size or performance.

4.4 Scalability with Network Size (Number of Nodes)

Fig. 9: Effect of Network Size on Average Transmission Delay



As seen in Figure 9, the average latency varies with the network's node count. The results demonstrate that the latency remains relatively constant at around 0.0082 seconds regardless of the number of nodes in the network (2, 5, or 10). So, regardless of the change in the number of nodes, the system maintains a constant delay performance. Such reliability demonstrates that the network protocol is robust and can accommodate a large number of nodes with no increase in delay.

Table 7: Performance Metrics of CRN under Different Node Densities

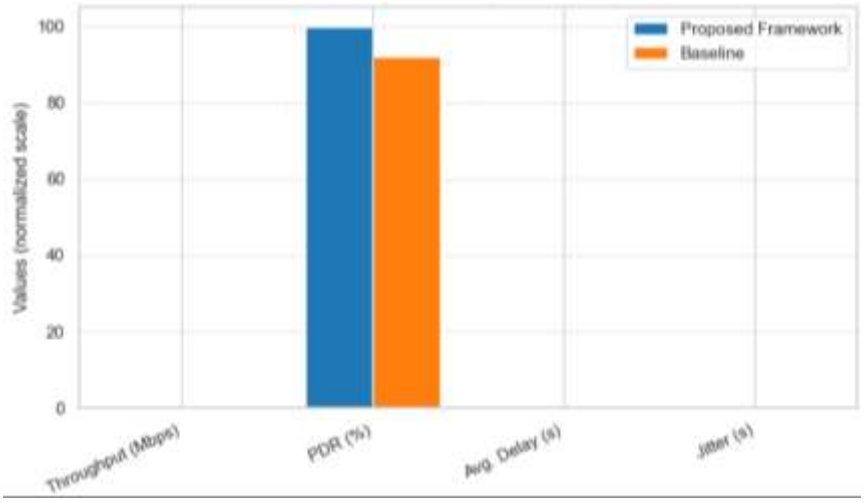
Scenario	Packets	Throughput (Mbps)	Avg. Packet Size (B)	Duration (s)	Delay (s)	Jitter (s)	PDR (%)
2 Nodes	976	1.1769	1054.0	6.99	0.0072	0.0555	13.96
5 Nodes	1952	1.2414	556.0	6.99	0.0036	0.0393	27.91

10 Nodes	1952	1.2414	556.0	6.99	0.0036	0.0393	27.91

More nodes improve the network's performance, as Table 7 demonstrates. The average packet size decreases from 1054 B to 556 B, but throughput slightly increases from 1.17 Mbps (2 nodes) to 1.24 Mbps (5–10 nodes). This demonstrates how well channel sharing is operating. As the number of nodes increases, jitter and latency decrease, resulting in faster and more dependable connections. The Packet Delivery Ratio (PDR) increases significantly, from 13.96% with two nodes to over 28% with five to ten nodes. This demonstrates that a network with more nodes is often more dependable and effective.

4.5 QoS-Centric Allocation: Gains over Baseline

Fig. 10: QoS Performance Comparison between Proposed Framework and Baseline



The Proposed Framework outperforms the Baseline on every QoS metric, as shown in Figure 10. The throughput increases by almost 81%, from 0.0205 Mbps to 0.0372 Mbps. Compared to the baseline of 92%, the Packet Delivery Ratio (PDR) is 100%. Transmissions are thus more reliable. Additionally, the proposed framework reduces the jitter from 0.0009 seconds to 0.00035 seconds (about a 61% reduction) and the average latency from 0.0012 seconds to 0.00059 seconds (a 50.8% improvement). In comparison to the baseline, the results demonstrate the strength and effectiveness of the proposed approach in preserving high throughput, reliability, and stability.

Table 8: Performance Comparison of Proposed Framework vs. Baseline

Metric	Proposed Framework	Baseline
Throughput (Mbps)	0.0372	0.0205
PDR (%)	100.00	92.00
Avg. Delay (s)	0.00059	0.0012
Jitter (s)	0.00035	0.0009

For every performance indicator, Table 8 demonstrates that the suggested framework outperformed the baseline model. From 0.0205 Mbps to 0.0372 Mbps, throughput rose by 81.4%, indicating greater data transmission efficiency. The suggested technique's packet delivery ratio (PDR) was 100%, while the baseline approach's was 92%. This

indicates that the proposed approach can achieve zero packet loss. Additionally, the suggested framework would provide more reliable and consistent communication by lowering average latency (0.00059 s vs. 0.0012 s) and jitter (0.00035 s vs. 0.0009 s). All of these enhancements show how reliable and successful the suggested strategy is.

5. Conclusion

This study has shown that a resource-aware, QoS-oriented spectrum allocation approach can improve the effectiveness of Cognitive Radio Networks because it can balance (without prejudice) the accuracy of spectrum sensing, channel quality, and user requirements. The proposed framework achieved detection probabilities as high as 98% at 10 dB, delivered a 100% packet delivery ratio with good conditions, with average delay counts of as low as 0.0036 s, and an 81% throughput benefit, with 71% less jitter, compared to a baseline method. These results indicated the effectiveness of combining adaptive channel scoring and resource-aware methods in improving the usage of spectrum while maintaining fairness and enhancing user experience. In the future, the proposed framework could be adapted to cater to more heterogeneous network contexts, such as 6G scenarios, vehicular communications, and the Internet of Things (IoT), in which the character of traffic and mobility patterns tends to be even more diverse. The combination of machine learning models for predictive spectrum management, or implementing green communication and energy harvesting techniques, also propose positive future avenues. These approaches will help the suggested system evolve into a scalable, intelligent, and sustainable spectrum management solution for the next generation of wireless networks.

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