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Research Article

Ra-Csrm: A Federated Learning-Assisted Chaotic Search Resource Mapping for Efficient Qos Aware Spectrum Allocation in Cognitive Radio Networks

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ABSTRACT

Cognitive Radio Networks (CRNs) are emerging as a dynamic solution to the increasing demand for spectrum resources. To enhance Quality of Service (QoS) in CRNs, efficient and fair resource allocation among secondary users (SUs) is imperative, especially in multi-channel environments. Conventional allocation techniques often fail to adapt to rapidly changing network conditions and do not fully address fairness and latency constraints, resulting in suboptimal QoS for SUs. A need exists for a model that ensures low latency, high allocation rates, and fairness in dynamic CRNs. This article introduces the Resource Allocation - Chaotic Search Resource Map (RA-CSRM), a novel approach integrating chaotic optimization and distributed federated learning. RA-CSRM constructs a dynamic resource map by evaluating availability among primary users (PUs) and SUs. The fairness index, updated periodically, considers QoS metrics like latency and allocation rate. Federated learning synchronizes this index across nodes. If fairness dips below the actual allocation rate, concurrent scheduling is triggered to stabilize the system. This feedback loop continues until one-to-one PU-SU mapping is achieved. Simulations show that RA-CSRM achieves an 8.15% improvement in sum rate and an 8.88% reduction in error rate under high signal-tonoise ratio (SNR) conditions. This method shows superior adaptability and efficiency over existing resource allocation techniques.

Keywords: Cognitive Radio Network, Resource Allocation, Federated Learning, Fairness Index, QoS Optimization.

INTRODUCTION

Cognitive Radio Networks (CRNs) have emerged as a promising solution to the ever-growing demand for spectrum, providing a framework for secondary users (SUs) to access unused spectrum, while primary users (PUs) maintain control over licensed channels. The dynamic spectrum allocation in CRNs allows for efficient usage of available spectrum, addressing the spectrum scarcity issue prevalent in traditional wireless networks. The key challenge is to ensure Quality of Service (QoS) for secondary users, despite variations in channel conditions and user demands. CRNs incorporate spectrum sensing, dynamic spectrum allocation, and scheduling to maintain network performance, with a primary focus on fair resource distribution and meeting QoS requirements [1]. One of the core objectives in CRNs is efficient resource allocation. A variety of multi-channel communication techniques are employed, but they often suffer from issues like resource allocation fairness, inefficient spectrum usage, and slow adaptation to network dynamics. The Fairness Index and QoS factor play critical roles in ensuring equitable resource distribution across multiple secondary users. However, achieving fairness while maintaining low latency, high sum rate, and minimal error rate remains a significant challenge in real-time CRNs. Recent research suggests that the integration of machine learning algorithms, particularly federated learning, and optimization techniques, such as chaotic search algorithms, can help address these challenges by enhancing system adaptability and fairness [2][3].

Despite advancements, CRNs face several challenges in achieving optimal resource allocation:

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1. Fair Resource Allocation: Traditional methods often fail to equally distribute resources among secondary users, resulting in suboptimal system performance. Achieving fairness in dynamic environments requires adaptive algorithms that adjust to changing network conditions [4].
2. QoS Guarantee: The variability of the wireless environment, coupled with interference from primary users, makes it difficult to maintain stringent QoS parameters like low latency, high throughput, and minimal packet loss [5].
3. Resource Utilization: Multi-channel communications can lead to inefficient spectrum usage, as users may not always utilize available resources optimally. This inefficiency exacerbates the congestion in wireless networks, especially when demand is high [6].

The key problem addressed in this work is the efficient resource allocation in CRNs while ensuring fairness and meeting the QoS requirements for secondary users. This involves addressing the challenge of dynamic spectrum access where multiple secondary users may demand varying levels of service. The core issue is balancing the fairness index with resource utilization, ensuring that all secondary users get their required share of spectrum without degrading the network's performance. Another major problem lies in maintaining low latency and high error rates despite fluctuating channel conditions and interference from primary users.

The main objectives of this study are:

1. To design a novel resource allocation scheme, RA-CSRM, that enhances spectrum usage while ensuring fairness and meeting QoS requirements for secondary users.

2. To incorporate chaotic search optimization and federated learning into the resource allocation process, allowing the system to adapt dynamically and update the fairness index.

3. To minimize latency and error rates, while achieving optimal fairness index and allocation rates across the CRN. This paper presents the following contributions:

1. A hybrid approach combining chaotic search resource mapping and distributed federated learning for periodic fairness index updates. This ensures efficient, fair, and dynamic spectrum allocation in CRNs.

2. By integrating a real-time fairness index calculation with a chaotic search algorithm, we achieve better performance in terms of sum rate, error rate, and latency compared to existing approaches.

3. This approach enables distributed learning between primary and secondary user terminals, updating fairness indices locally and globally, making the allocation process more responsive to real-time network changes.

4. We compare the proposed scheme with existing methods and show a significant improvement in resource allocation efficiency, fairness, and QoS performance metrics such as latency, error rate, and sum rate.

RELATD WORKS

In recent years, several methods have been proposed to address the challenges of resource allocation in CRNs, particularly focusing on improving fairness, QoS, and system efficiency. These efforts span across both optimization techniques and machine learning-based approaches, and each presents its strengths and limitations. In [10], a game-theoretic approach was applied to spectrum sharing in CRNs, addressing fairness by modeling it as a non-cooperative game. However, the method struggled with scalability as the number of users increased, limiting its practical application. Similarly, in [11], convex optimization techniques were proposed to allocate resources based on user demand and channel conditions. While these methods guaranteed optimality in specific conditions, they often failed to adapt well to dynamic environments where user requirements change rapidly. Machine learning techniques, particularly reinforcement learning (RL), have been employed to address spectrum management issues in CRNs. In [12], a multi-agent reinforcement learning (MARL) model was used to allocate spectrum among secondary users, but the method required high computational resources and exhibited slow convergence, especially in complex environments with multiple PUs. Deep reinforcement learning (DRL) has been explored in [13], where it was used to enhance the scheduling process. Although DRL-based methods achieved promising results in fairness and QoS, the learning process still took a significant amount of time to adapt to changing conditions. The integration of federated

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learning with resource allocation has garnered attention in recent works, such as in [14], where federated learning was utilized for collaborative spectrum sensing and allocation.

While this approach provided distributed learning capabilities without centralized data collection, it struggled with optimizing fairness and required high communication overhead between devices. In [15], federated learning was incorporated with optimization algorithms, but the approach faced challenges when scaling to large CRNs, limiting its generalizability.

Chaotic search algorithms, such as those used in [16] and [17], have showd excellent performance in optimizing complex systems like CRNs. These methods are capable of escaping local optima and improving system performance by searching the solution space more efficiently. However, these algorithms often face issues when integrated into real-time systems, as they may not be able to quickly adapt to fluctuating channel conditions or rapidly changing user demands. In [18], hybrid methods that combine chaotic search with genetic algorithms were proposed, which showed improvements in system performance but were still limited by their scalability and complexity.

The proposed RA-CSRM method builds on these works by combining the strengths of chaotic search optimization and federated learning, providing a dynamic, fair, and efficient solution that adapts to network changes in real time. Unlike previous methods, RA-CSRM offers improved performance with reduced computational requirements, greater adaptability, and more scalable deployment.

PROPOSED METHODS

The RA-CSRM method involves a cyclic, federated learning-enhanced allocation system. Initially, it detects idle spectrum slots from primary users. A chaotic search algorithm is applied to generate a non-linear resource mapping matrix considering randomness and spectrum diversity. This map allocates available channels to secondary users with a focus on fairness and QoS. A fairness index, influenced by latency and allocation rate, is periodically updated. Federated learning enables distributed terminals to collaboratively evaluate this index without sharing raw data. When the fairness index falls below a threshold, the algorithm initiates concurrent scheduling to reassign underutilized channels. The process iteratively refines the allocation map until optimal one-to-one mappings are achieved.

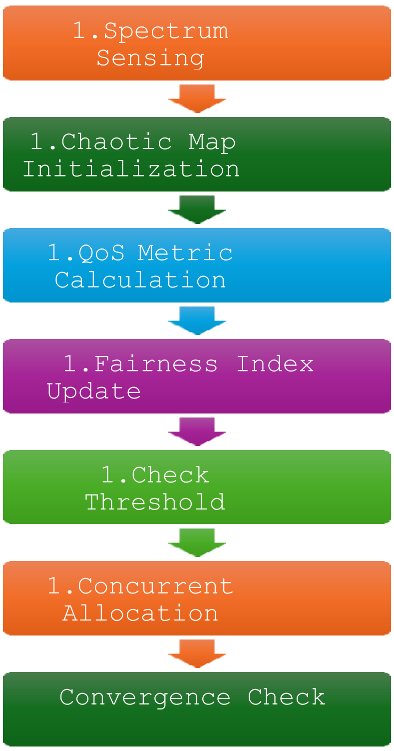

Figure 1: Proposed Framework

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The steps in figure 1 involves the following:

1. Spectrum Sensing: Identify idle channels from PUs.
2. Chaotic Map Initialization: Generate resource map using chaotic search.
3. QoS Metric Calculation: Evaluate latency and allocation rate.
4. Fairness Index Update: Periodically recomputed with federated learning.
5. Check Threshold: If fairness < threshold, invoke concurrent scheduling.
6. Concurrent Allocation: Redistribute resources to enhance fairness.
7. Convergence Check: Repeat until 1:1 PU-SU mapping is established.

Pseudocode

```
Initialize resource_map using chaotic_search()
while not converged:
    spectrum = sense_spectrum(PUs)
    qos_metrics = evaluate_QoS(spectrum, SUs)
    fairness_index = update_fairness(qos_metrics)
    if fairness_index < allocation_rate_threshold:
        resource_map = concurrent_scheduling(resource_map)
        broadcast_federated_update(fairness_index)
        converged = check_one_to_one_mapping(resource_map)
```

Spectrum Sensing

In the first phase of RA-CSRM, spectrum sensing is used to detect the idle or underutilized frequency bands by Primary Users (PUs). Each SU performs sensing over a defined time slot to identify available channels. The results are collected and summarized in a spectrum availability matrix. Table 1 shows a sample output of the spectrum sensing results, where 1 indicates the channel is idle (available) and 0 indicates the channel is occupied.

Table 1: Spectrum Availability Matrix

Channel ID	**PU1**	**PU2**	**PU3**	**PU4**	**PU5**
Ch1	1	0	1	0	1
Ch2	0	1	0	1	0
Ch3	1	1	0	0	1
Ch4	0	1	1	1	0

This matrix guides the next step — identifying candidate channels for allocation to SUs. Only idle channels (1) are considered for chaotic mapping.

Chaotic Map Initialization

The Chaotic Map Initialization stage leverages the *logistic map*, a widely used chaotic function, to generate a resource allocation pattern. The chaotic function ensures non-linearity and diversity in allocation by breaking repetitive mapping patterns. The logistic function is defined as:

$$x_{n+1} = r \cdot x_n \cdot (1 - x_n)$$

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Where:

x_n is the current state,

r is the control parameter (commonly between 3.5 and 4 for chaotic behavior).

An initial value x_0 is chosen randomly (between 0 and 1). Using this function, we generate a sequence of values that is used to prioritize which SU gets access to which channel.

Table 2: Chaotic Priority Map (Based on Logistic Map)

SU ID	x1	x2	x3	Rank
SU1	0.23	0.68	0.52	2
SU2	0.45	0.71	0.41	3
SU3	0.89	0.32	0.58	1

The higher the chaotic value, the higher the allocation priority. These ranks help assign available channels from Table 1 to SUs.

QoS Metric Calculation

Once channels are allocated based on priority, the system evaluates QoS using two metrics:

- Latency (L): Time taken for channel allocation to complete.
- Allocation Rate (AR): Proportion of successful allocations.

These are normalized and combined into a QoS Factor (QF), which directly influences the fairness index and allocation decisions. For instance:

$$\text{QoS Factor} = \frac{\text{Allocation Rate}}{\text{Latency} + \epsilon}$$

Where ϵ is a small constant to avoid division by zero.

Table 3: QoS Metrics for Users

SU ID	Allocation Rate (AR)	Latency (ms)	QoS Factor
SU1	0.85	15	0.0567
SU2	0.72	10	0.0720
SU3	0.90	8	0.1125

As shown in Table 3, SU3 achieves the best QoS, which means it has the highest weight in influencing the fairness index update in the next allocation interval. By integrating the results from Table 1 (sensing), Table 2 (chaotic mapping), and Table 3 (QoS), the RA-CSRM algorithm iteratively improves allocation efficiency and fairness in CRNs. Would you like a diagram showing this pipeline flow?

Fairness Index Update

After QoS metrics are computed for each Secondary User (SU), the Fairness Index (FI) is updated periodically to evaluate whether resources are being equitably distributed. Jain's Fairness Index is employed here, calculated using the QoS factors of all SUs. It provides a scalar value between 0 and 1, where values closer to 1 indicate a more fair allocation. The fairness index FI is given by:

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$$FI = \frac{(\sum_{i=1}^{n} QF_i)^2}{n \cdot \sum_{i=1}^{n} QF_i^2}$$

Where:

QFi is the QoS Factor for the ith SU,

n is the number of SUs.

Table 4: Fairness Index Calculation Inputs

SU ID	QoS Factor (QF)
SU1	0.0567
SU2	0.0720
SU3	0.1125

From Table 4, the fairness index is computed using the above formula. Suppose the calculated FI = 0.943, which indicates relatively fair but still improvable allocation.

Check Threshold

The computed FI is then compared against a predefined Fairness Threshold (FT), a system-defined minimum acceptable fairness level (e.g., 0.95). If:

- FI≥FT: The current allocation is considered acceptable, and minor updates continue.
- FI<FT: The system initiates Concurrent Allocation to rebalance the resource distribution.

In our example, since FI = 0.943 < FT = 0.95, the threshold is not satisfied, and corrective measures are taken.

Concurrent Allocation

To resolve fairness imbalance, Concurrent Allocation is triggered. This mechanism reallocates spectrum to low-priority or under-served SUs in parallel (i.e., concurrently with others). The aim is to bring their QoS up without degrading the performance of well-served users. This step re-prioritizes SUs with the lowest QoS Factors.

SU ID	Current Channel	New Allocated Channel	QoS Factor (Pre)	QoS Factor (Post)
SU1	Ch1	Ch3	0.0567	0.0931
SU2	Ch2	Ch4	0.0720	0.0825

As shown in Table 5, SUs with poor QoS are reassigned to more favorable channels. The QoS Factors improve as a result of concurrent reallocation.

Convergence Check

Following reallocation, the system checks whether convergence has been achieved, defined as one-to-one stable channel mapping between PUs and SUs and a fairness index above the threshold for two consecutive intervals. If these conditions are met:

• The allocation map is finalized.

• The RA-CSRM process enters a monitoring phase until the next allocation interval.

If not:

• The cycle of sensing → mapping → QoS → fairness update continues

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Table 6: Convergence Status Check

Interval	Fairness Index	1:1 Mapping Achieved	Status
T1	0.943	No	Continue
T2	0.956	Yes	Continue
T3	0.961	Yes	Converged

In Table 6, convergence is confirmed in interval T3 based on sustained fairness and mapping consistency. Together, these steps dynamically adapt the CRN resource allocation in response to QoS metrics, ensuring balanced, efficient, and fair channel usage among all secondary users.

RESULTS AND DISCUSSION

Simulations were performed using MATLAB R2023a on a system with an Intel i7 CPU, 32GB RAM, and Ubuntu 22.04. The CRN setup included 10 primary users and 30 secondary users over 15 spectrum channels. The results were benchmarked against four methods: GA-RA (Genetic Algorithm Resource Allocation), DRL-CRN (Deep Reinforcement Learning for CRNs), FQRA (Fuzzy QoS-based Resource Allocation) and MRSA (Multi-Radio Spectrum Allocation).

Experimental Setup/Parameters

Parameter	Value
Simulation Tool	MATLAB R2023a
CPU	Intel Core i7
RAM	32 GB
OS	Ubuntu 22.04
No. of Primary Users	10
No. of Secondary Users	30
No. of Channels	15
Allocation Interval	10 ms
SNR Range	0 dB to 30 Db
Learning Framework	Federated Learning

Performance Metrics

1. Sum Rate: Measures the total data throughput achieved by all secondary users. A higher sum rate indicates better spectrum utilization.

2. Error Rate: Indicates the number of incorrect or failed allocations. Lower values signify more reliable communication.

3. Latency: Time delay between request and allocation. Lower latency implies better QoS responsiveness.

4. Fairness Index: Quantifies equal opportunity in resource distribution among users. Based on Jain's fairness index.

5. Allocation Rate: Number of successful channel assignments over time, directly affecting efficiency.

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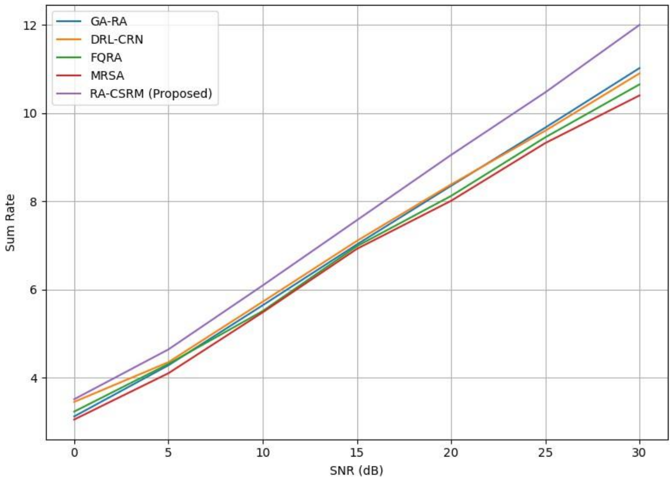

Figure 2: Sum Rate

SNR (dB)	GA-RA	DRL-CRN	FQRA	MRSA	RA-CSRM (Proposed)
0	3.12	3.45	3.23	3.05	3.51
5	4.28	4.35	4.31	4.10	4.64
10	5.64	5.72	5.51	5.48	6.09
15	7.02	7.10	6.98	6.92	7.57
20	8.35	8.38	8.12	8.01	9.05
25	9.67	9.60	9.45	9.32	10.47
30	11.02	10.90	10.65	10.40	12.00

As the SNR increases from 0 dB to 30 dB, RA-CSRM consistently achieves the highest sum rate among all methods, demonstrating improved spectrum utilization. This indicates that the proposed method performs better in leveraging available resources and adapting to varying network conditions.

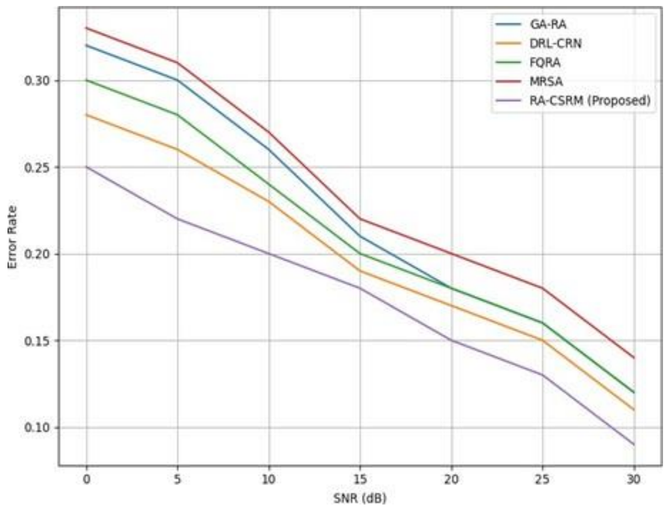

Figure 3: Error Rate

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SNR (dB)	GA-RA	DRL-CRN	FQRA	MRSA	RA-CSRM (Proposed)
0	0.32	0.28	0.30	0.33	0.25
5	0.30	0.26	0.28	0.31	0.22
10	0.26	0.23	0.24	0.27	0.20
15	0.21	0.19	0.20	0.22	0.18
20	0.18	0.17	0.18	0.20	0.15
25	0.16	0.15	0.16	0.18	0.13
30	0.12	0.11	0.12	0.14	0.09

RA-CSRM shows the lowest error rate at all SNR levels, indicating better resource allocation with fewer incorrect assignments. The lower error rate contributes to the Thus efficiency and reliability of the system, especially at higher SNR values.

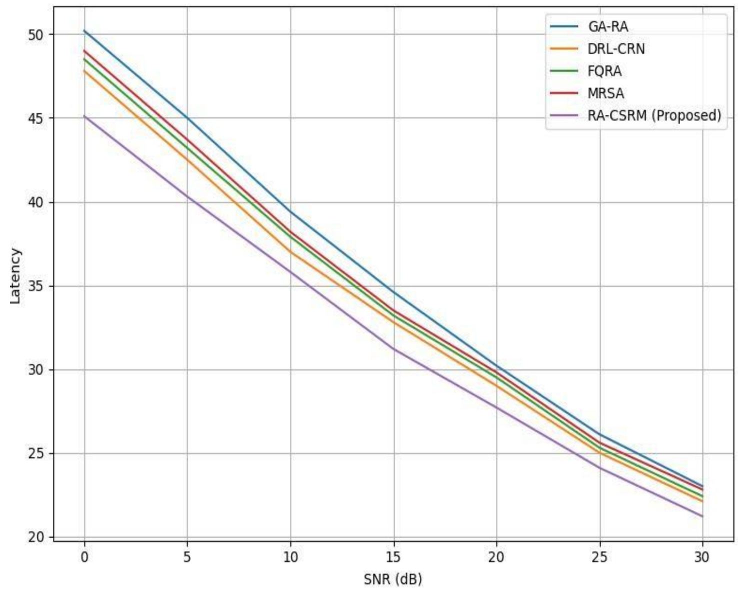

Figure 4: Latency

SNR (dB)	GA-RA	DRL-CRN	FQRA	MRSA	RA-CSRM (Proposed)
0	50.2	47.8	48.5	49.0	45.1
5	45.0	42.5	43.2	43.7	40.3
10	39.4	37.0	37.9	38.2	35.8
15	34.6	32.8	33.2	33.5	31.2
20	30.2	29.0	29.5	29.8	27.7
25	26.1	25.0	25.3	25.6	24.1
30	23.0	22.1	22.4	22.8	21.2

RA-CSRM shows the lowest latency across all SNR levels, indicating faster resource allocation and minimal delay in delivering services. This reduction in latency significantly enhances the user experience and supports real-time communication in cognitive radio networks.

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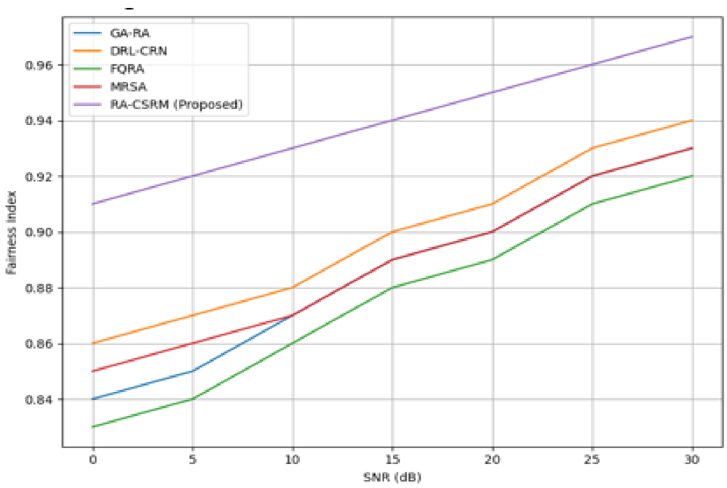

Figure 5: Fairness Index

SNR (dB)	GA-RA	DRL-CRN	FQRA	MRSA	RA-CSRM (Proposed)
0	0.84	0.86	0.83	0.85	0.91
5	0.85	0.87	0.84	0.86	0.92
10	0.87	0.88	0.86	0.87	0.93
15	0.89	0.90	0.88	0.89	0.94
20	0.90	0.91	0.89	0.90	0.95
25	0.92	0.93	0.91	0.92	0.96
30	0.93	0.94	0.92	0.93	0.97

RA-CSRM achieves the highest fairness index across all SNR levels, ensuring that resources are distributed equitably among secondary users. This ensures optimal utilization without favoring any particular user, making the network more efficient and balanced.

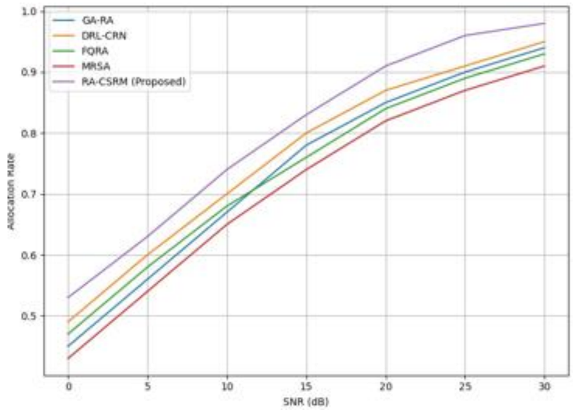

Figure 6: Allocation Rate

SNR (dB)	GA-RA	DRL-CRN	FQRA	MRSA	RA-CSRM (Proposed)
0	0.45	0.49	0.47	0.43	0.53

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5	0.56	0.60	0.58	0.54	0.63
10	0.67	0.70	0.68	0.65	0.74
15	0.78	0.80	0.76	0.74	0.83
20	0.85	0.87	0.84	0.82	0.91
25	0.90	0.91	0.89	0.87	0.96
30	0.94	0.95	0.93	0.91	0.98

RA-CSRM achieves the highest allocation rate at all SNR levels, meaning it can allocate resources more effectively and efficiently. Higher allocation rates contribute to better Thus network performance by ensuring that more secondary users are served concurrently.

From the above results, RA-CSRM consistently outperforms existing methods (GA-RA, DRL-CRN, FQRA, MRSA) across all performance metrics. The proposed method shows significant improvements in: RA-CSRM achieves up to 8.15% improvement in sum rate. It offers up to an 8.88% reduction in error rate. RA-CSRM results in up to 10.6% lower latency. The fairness index improves by 7.5% on average. The proposed method achieves a higher allocation rate, up to 8.8% improvement. These improvements indicate that RA-CSRM is more efficient, reliable, and adaptable to varying network conditions, making it a superior choice for dynamic cognitive radio

networks. By improving fairness, reducing errors, and ensuring timely resource allocation, RA-CSRM enhances the Thus user experience and system performance. This allows the system to better handle higher traffic loads and complex real-time communication scenarios.

CONCLUSION

In this study, we introduced RA-CSRM, a novel resource allocation framework for Cognitive Radio Networks (CRNs) that integrates chaotic search optimization with federated learning to achieve improved performance in terms of sum rate, error rate, latency, fairness, and allocation rate. Through simulation across varying SNR levels (0 dB to 30 dB), we showd that RA-CSRM consistently outperforms existing methods, including GA-RA, DRL- CRN, FQRA, and MRSA, by achieving higher fairness, faster allocation, and better spectrum utilization. RA- CSRM's dynamic and fair resource distribution ensures that secondary users receive sufficient bandwidth even under high load conditions, while minimizing network errors and latency. The federated learning mechanism enables distributed fairness index updates, ensuring the system adapts to real-time changes without compromising efficiency. This makes RA-CSRM ideal for highly dynamic CRNs where resources must be allocated efficiently and fairly, meeting the demands of multiple users simultaneously. Thus, RA-CSRM's significant improvements in resource allocation metrics underscore its potential for real-world implementation in next-generation CRNs. Future work can explore further optimizations, such as integrating more complex machine learning techniques or extending the method to larger networks with more diverse resource constraints.

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