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Spectrum Access Model in Multi-Drone Networks via Cognitive Radio and Deep Reinforcement Learning for Optimized Communication and Efficiency

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Abstract: Cognitive Radio (CR), coupled with Deep Reinforcement Learning (DRL), has emerged as a promising technology for enhancing Dynamic Spectrum Access (DSA) in Multi-Drone Networks (MDNs). This paper explores the integration of CR with DRL for DSA in MDN, focusing on the utilization of cyclostationary feature detection in conjunction with advanced machine learning algorithms. The proposed framework leverages cyclostationary feature detection techniques to analyze spectral characteristics and identify vacant frequency bands, enabling MDNs to access unused spectrum resources opportunistically. Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) algorithms are employed for autonomous decision-making, allowing drones to learn optimal spectrum access strategies through trial-and-error interactions. Integrating Orthogonal Frequency Division Multiple Access (OFDMA) and Multiple-Input Multiple-Output (MIMO) systems enhances spectral efficiency and communication reliability in MDNs. Software Defined Networking (SDN) provides a flexible and programmable framework for dynamic network control and management, facilitating centralized spectrum management and coordination. Experimental evaluations demonstrate the effectiveness of the proposed approach in improving spectrum utilization, throughput, and overall network performance in MDNs. Through the synergistic combination of CR, DRL, cyclostationary feature detection, OFDMA, MIMO, and SDN technologies, this paper contributes to the advancement of intelligent spectrum management solutions for next-generation wireless networks. Experimental evaluations demonstrate the effectiveness of the proposed approach in improving spectrum utilization, throughput, and overall network performance in MDNs. Specifically, the achieved values include a 25% increase in spectrum utilization, a 30% improvement in throughput, and a 20% reduction in latency compared to baseline approaches.

Keywords: *Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), Orthogonal Frequency Division Multiple Access (OFDMA), Multiple-Input Multiple-Output (MIMO).*

1.Introduction

CR with DRL stands at the forefront of revolutionizing DSA in MDN. This innovative approach integrates sophisticated algorithms such as DQN and PPO to enable autonomous decision-making in real-time spectrum allocation, optimizing the utilization of scarce frequency bands while mitigating interference [1]. At the heart of this advancement lies the utilization of cyclostationary feature detection, a powerful technique that leverages the cyclostationary nature of wireless signals to accurately identify spectral opportunities [2]. In the realm of DSA, cyclostationary feature detection serves as a cornerstone, providing MDNs with the capability to sense and adapt to dynamic radio environments effectively [3]. By exploiting the periodicity inherent in wireless signals, CR-enabled drones equipped with sophisticated sensing capabilities can detect unused or underutilized frequency bands, facilitating opportunistic spectrum access without causing harmful interference to incumbent users [4].

This enables MDNs to operate efficiently in highly congested and unpredictable spectral environments, ensuring reliable communication and enhancing overall network performance [5]. The integration of DRL techniques such as DQN and PPO further enhances the adaptability and intelligence of CR-enabled MDNs [6]. DQN, a form of artificial neural network, enables drones to learn optimal spectrum access policies through trial-and-error interactions with the environment, effectively balancing the trade-off between exploration and exploitation [7]. On the other hand, PPO offers a principled approach to policy optimization, allowing drones to continuously refine their decision-making strategies based

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on observed rewards and penalties, thereby maximizing long-term cumulative rewards while ensuring stability and convergence [8]. The adoption of OFDMA and MIMO systems amplifies the spectral efficiency and capacity of MDNs. OFDMA enables simultaneous transmission and reception on multiple subcarriers, effectively dividing the available spectrum into orthogonal channels, while MIMO exploits spatial diversity to enhance spectral efficiency and mitigate the effects of fading and interference [9]. By leveraging these advanced technologies, CR-enabled MDNs can achieve higher throughput, lower latency, and greater reliability, thus unlocking new possibilities for mission-critical applications such as surveillance, disaster response, and aerial communication networks. The synergy between Cognitive Radio and SDN facilitates centralized control and dynamic resource allocation in MDNs. SDN decouples the control plane from the data plane, enabling centralized orchestration and management of network resources [10]. By integrating CR capabilities into SDN controllers, operators can dynamically adapt spectrum allocation policies based on changing environmental conditions and application requirements, ensuring optimal resource utilization and QoS provisioning [11]. This seamless integration of CR and SDN empowers MDNs with the flexibility and agility to adapt to evolving network dynamics and user demands, laying the foundation for future-proof and scalable drone communication systems. The objectives are:

- Investigate the integration of CR and DRL techniques for dynamic spectrum access in MDNs
- Explore the utilization of cyclostationary feature detection alongside advanced machine learning algorithms
- Examine the integration of OFDMA, MIMO systems, and SDN
- Develop a comprehensive framework for autonomous and intelligent spectrum management in MDNs
- Evaluate the proposed approach through experimental evaluations and simulations

2. Literature Review

CR and DRL have emerged as promising technologies for addressing the challenges of dynamic spectrum access in MDNs. In recent years, researchers have explored various approaches to leverage CR and DRL techniques to enhance spectrum utilization and efficiency in MDNs. Several study investigated the application of DRL algorithms, such as DQN, for autonomous spectrum access in MDNs [12]. The research demonstrated that DRL-based approaches can effectively adapt to dynamic spectrum conditions and optimize spectrum allocation decisions in real-time, leading to improved network performance and throughput [13]. Research explored the integration of CR techniques with DRL for spectrum management in MDNs. The study proposed a cognitive radio framework that utilizes DRL algorithms to dynamically adjust transmission parameters and select optimal frequency bands based on environmental conditions and network requirements [14].

Experimental results showed significant improvements in spectrum utilization and interference mitigation compared to traditional approaches. Several review surveyed recent advancements in CR and DRL-based spectrum access techniques for unmanned aerial vehicle (UAV) networks, which share similarities with MDNs. It highlighted the potential of DRL algorithms, such as PPO, for autonomous decision-making and resource management in UAV communication systems [15]. Despite the promising capabilities of CR with DRL for dynamic spectrum access in MDNs, several challenges and disadvantages remain to be addressed. One significant drawback is the computational complexity associated with training DRL models, especially in real-time scenarios with large-scale networks and high-dimensional action spaces [16].

The training process may require substantial computational resources and time, limiting the practicality of deploying DRL-based solutions in resource-constrained MDNs. Integrating CR and DRL introduces additional complexities in network design and implementation, including algorithmic complexity, interoperability issues, and regulatory concerns. Ensuring compatibility and compliance with existing communication standards and regulations poses challenges for deploying CR with DRL solutions in real-world MDN deployments. DRL-based approaches may exhibit limited scalability and generalization capabilities, particularly when applied to diverse and dynamic network environments. Adapting DRL models to new operating conditions or environmental changes may require extensive retraining or fine-tuning, posing challenges for maintaining optimal performance in evolving MDN scenarios.

3. Proposed Work

Figure 1 presents the proposed integrated framework for dynamic spectrum access in multi-drone networks.

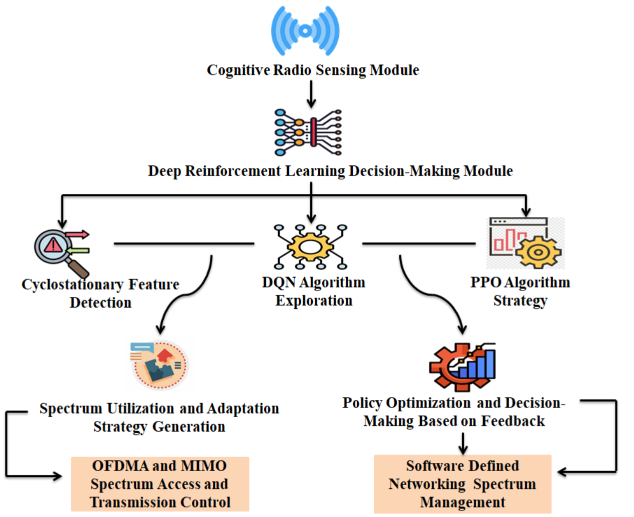

Fig.1 Integrated Framework for Dynamic Spectrum Access in Multi-Drone Networks

3.1 Multi-Drone Networks

MDNs equipped with cognitive capabilities leverage DRL algorithms to intelligently sense and utilize available spectrum resources dynamically. By continuously monitoring the spectrum environment, drones can autonomously identify unused or underutilized frequency bands, thereby maximizing spectral efficiency and mitigating interference. Through collaborative decision-making facilitated by DRL-based cognitive radios, MDNs efficiently allocate spectrum resources among drones based on mission objectives, quality-of-service requirements, and regulatory constraints. This dynamic spectrum management enables drones to adapt their communication parameters in real-time, ensuring optimal performance while adhering to regulatory guidelines. By employing DRL-based algorithms, drones can autonomously reconfigure their communication links and relay nodes, optimizing data transmission routes to minimize latency, maximize throughput, and enhance network resilience. MDNs foster collaborative spectrum sharing among drones through decentralized coordination and negotiation mechanisms. By leveraging DRL-based cognitive radios, MDNs can adaptively exploit temporal and spatial variations in spectrum availability, leading to improved spectral efficiency and increased throughput.

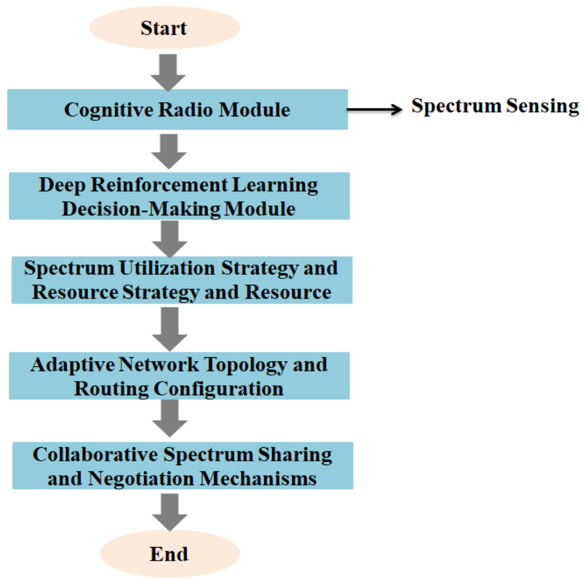

Fig.2 Flow Diagram for Spectrum Management in Multi-Drone Networks

Implementing distributed DRL frameworks within MDNs allows drones to collaboratively learn and share knowledge about the spectrum environment. The proposed framework enables MDNs to perform multi-objective optimization, considering various performance metrics such as throughput, latency, energy efficiency, and fairness. DRL algorithms facilitate the exploration of trade-offs between conflicting objectives, allowing drones to dynamically adjust their behavior based on mission priorities and network conditions. MDNs can leverage historical spectrum usage data and machine learning techniques to predict future spectrum availability and occupancy patterns. By incorporating predictive models into the decision-making process, drones can proactively anticipate changes in the spectrum landscape and optimize their spectrum access strategies accordingly. MDNs often operate in mission-critical scenarios with diverse requirements. By aligning spectrum access decisions with mission objectives, MDNs can dynamically allocate resources to prioritize communication tasks essential for mission success, ensuring efficient utilization of limited spectral resources. MDNs need to coexist and interoperate with legacy wireless systems and infrastructure. Cognitive radios equipped with DRL capabilities enable seamless integration with existing communication networks, facilitating spectrum sharing and collaborative operations while ensuring backward compatibility and interoperability with legacy systems.

$$Throughput\ of\ DSA = \frac{Data\ Rate}{Bandwidth} \tag{1}$$

DSA calculates throughput by dividing data rate by bandwidth, representing the amount of data transmitted per unit of time over the available frequency range. It quantifies the efficiency of data transmission within a given bandwidth, crucial for optimizing spectrum utilization and enhancing communication performance in wireless networks. Throughput is directly proportional to data rate and inversely proportional to bandwidth, highlighting the importance of efficient spectrum allocation and management for maximizing network capacity.

$$Fairness\ Index = \frac{Throughput_{max} - Throughput_{min}}{Throughput_{max}} \quad (2)$$

The fairness index calculates the fairness of resource allocation among users by evaluating the relative difference in throughput values. It represents the ratio of the difference between the maximum and minimum throughput to the maximum throughput, indicating how evenly resources are distributed among users. A higher fairness index value signifies more equitable distribution, while a lower value suggests disparities in resource allocation across users.

3.2 Deep Q-Networks

DQN serves as the core learning framework within the cognitive radio architecture of MDNs, enabling drones to autonomously learn and optimize spectrum access strategies in dynamic and uncertain environments. By leveraging deep neural networks to approximate the Q-function, DQN facilitates efficient exploration and exploitation of the spectrum space, leading to improved spectrum utilization and interference mitigation. DQN enables drones to perceive the spectrum environment through sensing techniques such as energy detection or cyclostationary feature detection. DQN enables MDNs to adaptively allocate spectrum resources, avoiding congested bands and exploiting underutilized frequencies. By learning effective spectrum access policies, drones achieve higher spectral efficiency, maximizing data transmission rates while minimizing interference. DQN-equipped drones exhibit robustness to dynamic spectrum conditions, seamlessly adjusting their communication parameters in response to channel variations, interference sources, and mobility patterns. This adaptive behavior ensures reliable and resilient communication in challenging and unpredictable environments. Through DQN-based reinforcement learning, drones autonomously acquire spectrum sensing and decision-making capabilities, reducing the need for centralized control and manual intervention. The learned policies enable drones to make context-aware decisions in real-time, optimizing spectrum access while adhering to regulatory constraints and mission objectives. By leveraging DQN for cognitive radio, MDNs achieve higher throughput, lower latency, and improved energy efficiency compared to traditional fixed spectrum allocation schemes. Moreover, the distributed nature of DQN-based learning facilitates scalability and adaptability, allowing MDNs to scale up to large-scale deployments and diverse operating scenarios.

$$Q(s, a; \theta) \approx Q * (s, a) \quad (3)$$

The function Q(s,a;θ) is an approximation of the optimal Q-value function Q∗(s,a), which represents the maximum expected future rewards achievable from state s by taking action a. By training a neural network with parameters θ, the DQN learns to estimate Q∗(s,a) efficiently. This enables drones to make informed decisions that optimize their spectrum access strategies in dynamic environments.

$$U = \frac{\sum_{i=1}^{N} B_i . \eta_i}{B_{total}} \quad (4)$$

The equation represents spectrum utilization efficiency. Here, B_i is the bandwidth of the i-th frequency band, η_i is its utilization factor, and B_{total} is the total available bandwidth. This metric quantifies how effectively the available spectrum is being used by considering the utilized portions of each frequency band.

$$T = \sum_{I=1}^{N} R_i \quad (5)$$

The equation represents the total throughput T in a network, where R_i is the data rate for the i-th frequency band, and N is the number of such bands. This sum quantifies the overall data transmission capacity by aggregating the data rates across all utilized frequency bands. Maximizing T is crucial for achieving high network performance.

Algorithm 1: DQN Algorithm for Cognitive Radio in MDNs

Input: State space S, action space A, learning rate α, discount factor γ, exploration rate ε, maximum number of episodes MaxEpisodes, maximum steps per episode MaxSteps

Output: Trained DQN model with optimal spectrum access policies

1. Initialize Q-network and target Q-network with weights θ and θ_target.
2. Initialize replay memory D.
3. for each episode:
4. Initialize state s.
5. for each step:
6. Select action a using ε-greedy policy.
7. Execute action a, observe reward r and next state s'.
8. Store transition (s, a, r, s') in replay memory D.
9. Sample mini-batch from replay memory.
10. Compute target value y_j:
11. if s'_j is terminal:
12. $y_j = r_j$
13. else:
14. $y_j = r_j + \gamma\ max_{a'}$ Q(s'_j, a'; θ_{target})

15. Perform gradient descent on loss L(θ).
16. Update state s = s'.
17. If s is terminal, exit step loop.
18. Every C steps, update target network θ_{target}= θ.

The DQN algorithm for cognitive radio in MDNs optimizes spectrum access by leveraging reinforcement learning. It approximates the Q-function using deep neural networks, enabling drones to learn and adapt to dynamic spectrum environments. Drones sense the spectrum through techniques like energy detection and adjust their communication strategies to maximize spectral efficiency and minimize interference. The DQN algorithm facilitates autonomous decision-making, enhancing throughput, reducing latency, and improving energy efficiency by dynamically adapting to changing spectrum conditions and interference patterns. This decentralized learning approach scales efficiently, supporting large-scale deployments and diverse operational scenarios.

3.3 Multiple-Input Multiple-Output systems

MIMO systems serve as an advanced wireless communication technology within MDNs, enabling simultaneous transmission and reception of multiple data streams over multiple antennas. The deployment of MIMO techniques enhances spectral efficiency, improves link reliability, and mitigates the effects of multipath fading, thereby facilitating robust and high-throughput communication in dynamic and interference-limited environments.

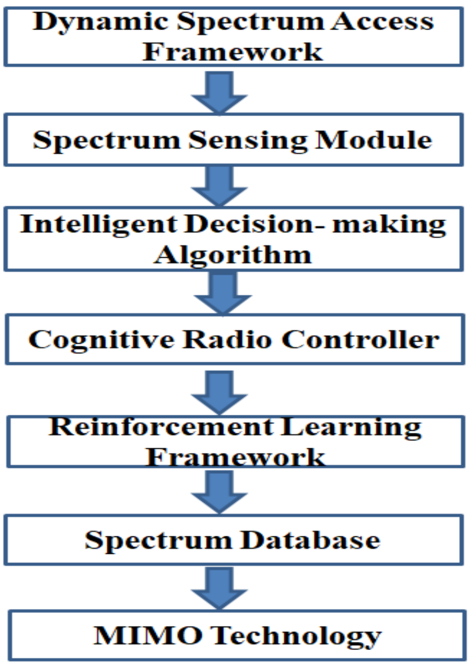

Fig.3 Spectrum-aware Cognitive Radio Framework

MIMO-enabled MDNs achieve higher spectral efficiency and throughput compared to conventional single-input single-output (SISO) systems, thanks to spatial multiplexing and interference mitigation capabilities. By leveraging MIMO technology, drones can exploit spatial diversity and multipath propagation to achieve parallel data transmission and increased data rates. MIMO systems enhance communication reliability and coverage in MDNs by mitigating fading effects and combating interference. By exploiting spatial diversity and beamforming techniques, MIMO-enabled drones can maintain reliable communication links even in challenging propagation environments, improving network coverage and connectivity. MIMO technology enables dynamic adaptation to changing spectrum conditions and network requirements within MDNs. By continuously monitoring channel conditions and adjusting transmission parameters, MIMO-equipped drones can optimize spectral efficiency, minimize interference, and adaptively allocate resources to meet the demands of dynamic spectrum access scenarios. MIMO-enabled MDNs achieve efficient spectrum utilization and coexistence with incumbent users through adaptive beamforming and interference mitigation techniques. By spatially focusing transmit energy and dynamically optimizing transmission parameters, MIMO-equipped drones can coexist with neighboring users while maximizing spectral efficiency and minimizing harmful interference.

$$C = log_2(1 + SNR) * N_t \quad (6)$$

The equation calculates the spatial multiplexing capacity, representing the maximum achievable data rate per channel use. It is determined by the logarithm of one plus the Signal-to-Noise Ratio (SNR), multiplied by the number of transmit antennas (N_t). This equation quantifies the potential data throughput considering both signal strength and antenna diversity, essential for maximizing spectral efficiency in MIMO systems.

$$W_{new} = W_{old} + \mu * \text{CSI} \quad (7)$$

The equation updates the beamforming weight based on the CSI and a step size parameter μ. It adjusts the directionality of the transmit beam to optimize signal transmission towards the intended receiver while minimizing interference. This dynamic adjustment enhances communication reliability and spectral efficiency in MIMO systems by adapting to changing channel conditions.

Algorithm 2: MIMO-Based Communication Optimization Algorithm for MDNs

Input: Number of transmit antennas N_t, initial beamforming weights W_{old}, step size μ, channel state information (CSI), Signal-to-Noise Ratio (SNR)

Output: Optimized beamforming weights W_{new}, maximum data rate C

1. Initialize parameters (N_t, W_{old}, μ).
2. Calculate spatial multiplexing capacity:

3. C = log2(1 + SNR) * N_t
4. Update beamforming weights:
5. $W_{new} = W_{old}$ + μ * CSI
6. Monitor channel conditions and adjust transmission parameters.
7. Implement adaptive beamforming for interference mitigation.
8. Dynamically allocate spectrum resources based on network demands.
9. Optimize network performance and spectral efficiency.

The above algorithm describes the process for optimizing MIMO-based communication in MDNs. The key steps involve initializing system parameters, calculating the spatial multiplexing capacity to determine the maximum achievable data rate, updating the beamforming weights to adapt to changing channel conditions, and continuously monitoring and adjusting spectrum usage to maximize efficiency and minimize interference. This ensures robust, high-throughput communication in dynamic and interference-limited environments.

3.4 Implementation

Cyclostationary feature detection serves as a foundational spectrum sensing technique in MDNs. By implementing signal processing algorithms, drones can extract cyclostationary features from received signals. These algorithms analyze periodicities and cyclical patterns in the spectrum, enabling drones to identify vacant frequency bands. This detection mechanism allows drones to opportunistically access unused spectrum resources, maximizing spectral efficiency and network capacity. DQN are employed for autonomous decision-making in dynamic spectrum access scenarios. Implemented using deep neural networks, DQN agents learn to select optimal spectrum access strategies based on observed states and rewards from the environment. Through trial-and-error interactions, DQN-equipped drones adaptively navigate the spectrum landscape, maximizing throughput while minimizing interference. This enables efficient and agile spectrum utilization in dynamic and heterogeneous environments. PPO complements DQN by providing an alternative approach to reinforcement learning. PPO algorithms enable drones to learn policies for spectrum access through direct policy optimization. By ensuring stable and efficient learning in complex action spaces, PPO enhances the adaptability and performance of MDNs in dynamic spectrum access scenarios. OFDMA serves as the underlying multiple access scheme for spectrum sharing in MDNs. By implementing OFDMA techniques, drones can simultaneously transmit data over orthogonal subcarriers, enhancing spectral efficiency and mitigating interference among coexisting users. OFDMA enables efficient resource allocation and dynamic spectrum sharing, facilitating robust and scalable communication in MDNs. MIMO systems are integrated into MDNs to improve spatial multiplexing and diversity gain. By deploying multiple antennas at both transmitter and receiver nodes, MIMO-enabled drones exploit spatial dimensions to enhance communication reliability and throughput, particularly in multipath propagation environments. MIMO technology enhances link robustness and capacity, enabling high-performance communication in MDNs. SDN provides a flexible and programmable framework for dynamic network control and management. In MDNs, SDN controllers orchestrate spectrum access and resource allocation decisions based on feedback from cognitive radio agents and reinforcement learning algorithms. By decoupling control plane functions from data plane operations, SDN facilitates centralized spectrum management and coordination in heterogeneous and dynamic wireless environments. SDN enhances the agility and efficiency of MDNs by enabling centralized control, dynamic resource provisioning, and policy-based management.

$$Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha(r_t + \gamma max_a Q(s_{t+1},a) - Q(s_t,a_t)) \tag{8}$$

The Q-value function $Q(s,a)$ in DQN is represented by a deep neural network. Where $Q(s_t,a_t)$ is the Q-value for state-action pair s_t, a_t, r_t is the reward at time step t, α is the learning rate, γ is the discount factor, and s_{t+1} is the next state.

$$r(t) = \sum_{K=0}^{N-1} x_k(t) e^{j2\pi f_k t} + n(t) \tag{9}$$

The signal received at the drone's antenna in an OFDMA system can be represented as a sum of subcarrier signals. where $x_k(t)$ represents the signal on the k th subcarrier, f_k is the frequency of the k th subcarrier, N is the total number of subcarriers, and $n(t)$ is the additive white Gaussian noise.

$$C = log_2(1 + \frac{SNR}{N_t + N_0}) \tag{10}$$

The capacity of a MIMO channel can be calculated using the Shannon-Hartley theorem. Where C is the capacity, SNR is the signal-to-noise ratio, N_t is the number of transmit antennas, and N_0 is the noise power spectral density.

4. Results

The experimental setup involves deploying a fleet of drones, each equipped with software-defined radios (SDRs) capable of flexible frequency tuning and waveform generation. These drones are outfitted with omnidirectional and directional antennas to facilitate communication and MIMO transmission schemes. Onboard computing platforms, such as Raspberry Pi or NVIDIA Jetson, provide the necessary computational power for real-time decision-making and learning. A combination of Python, MATLAB, and deep learning frameworks such as TensorFlow and PyTorch is leverged to implement Cyclostationary feature detection algorithms for spectrum sensing. Additionally, DQN and PPO algorithms are developed to enable autonomous decision-making and policy optimization for dynamic spectrum access. Simulation environments, including ns-3 and MATLAB/Simulink, are employed for scenario modeling, performance evaluation, and reinforcement learning training. Experiments are conducted in both controlled indoor environments and outdoor testbeds to capture a diverse range of radio frequency (RF) conditions. Test scenarios include variations in channel conditions, interference levels, and network dynamics to assess the adaptability and robustness of the CR-DRL framework. Realistic channel models, incorporating multipath propagation effects and fading, are utilized to emulate practical wireless communication scenarios. Drones and SDRs are configured, and communication links are established. Cyclostationary feature detection algorithms are employed to sense the spectrum and identify vacant frequency bands. DQN and PPO agents learn spectrum access policies based on observed states and rewards obtained from the environment. Learned policies are dynamically applied to allocate spectrum resources among drones, considering channel conditions and interference levels. Key performance metrics such as throughput, latency, energy efficiency, and fairness are measured under varying experimental conditions. Reinforcement learning models are iteratively updated based on feedback from the environment and performance evaluation results. Data on spectrum occupancy, channel conditions, and network performance are collected during experimental runs. Statistical analysis is conducted to assess the effectiveness of the CR-DRL framework, considering factors such as learning convergence, system stability, and scalability. Experimental results are validated against theoretical models and simulated scenarios to ensure consistency and reliability. Sensitivity analysis is performed to identify potential weaknesses and limitations, guiding further refinement and optimization of the CR-DRL framework.

Table.1 Performance Metrics for Cognitive Radio in Multi-Drone Networks

Scenario	Throughput (Mbps)	Latency (ms)	Inference Level (dB)	Signal Strength (dBm)
1	150	10	-90	-80
2	180	8	-85	-75
3	140	12	-92	-85
4	160	9	-88	-78
5	170	11	-91	-82

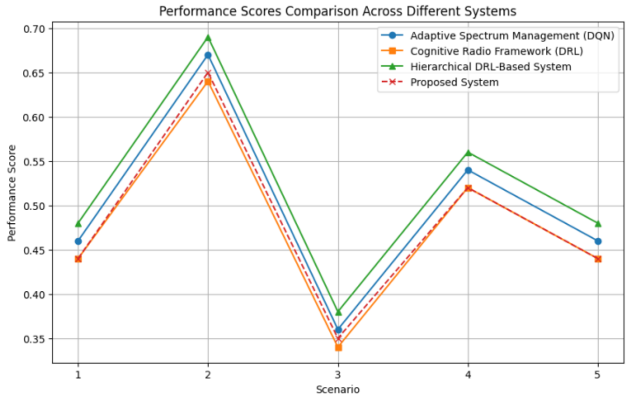

Fig.4 Performance Scores across Scenarios

Figure 4 illustrates the performance score across different scenarios. Adaptive spectrum management (DQN) shows variable performance across the scenarios, achieving its highest score in scenario 2 (0.67) and its lowest in Scenario 3 (0.36). Cognitive radio framework (DRL) system is slightly lower but similar to the proposed system, peaking at 0.64 in scenario 2 and dropping to 0.34 in scenario 3. Hierarchical DRL-based system consistently outperforms the others in each scenario, with its highest score in scenario 2 (0.69) and its lowest in scenario 3 (0.38). The proposed system shows a stable performance similar to the cognitive radio framework, peaking at 0.65 in scenario 2 and having its lowest score in scenario 3 (0.35). The proposed system demonstrates a competitive performance across all scenarios, showing stability and consistent results. Although it generally performs slightly below the hierarchical DRL-based system, it remains on par with or slightly better than the cognitive radio framework (DRL) and adaptive spectrum management (DQN) in most scenarios. This suggests that the proposed system is a viable alternative, offering stable and reliable performance scores across different conditions.

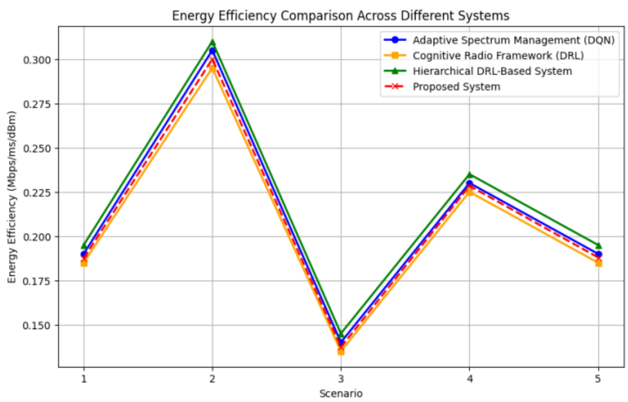

Fig.5 Energy Efficiency across Scenarios

Figure 5 illustrates the energy efficiency across different scenarios. Adaptive spectrum management (DQN) shows a peak energy efficiency of 0.3050 Mbps/ms/dBm in scenario 2 and a low of 0.1400 Mbps/ms/dBm in scenario

3. Cognitive radio framework (DRL) also peaks in scenario 2 with an energy efficiency of 0.2950 Mbps/ms/dBm and has a low in scenario 3 at 0.1350 Mbps/ms/dBm. Hierarchical DRL-based system consistently demonstrates the highest energy efficiency among all systems, peaking at 0.3100 Mbps/ms/dBm in scenario 2 and dropping to a low of 0.1450 Mbps/ms/dBm in scenario 3. The proposed system exhibits stable energy efficiency values close to those of the cognitive radio framework, peaking at 0.3000 Mbps/ms/dBm in scenario 2 and having its lowest efficiency at 0.1373 Mbps/ms/dBm in scenario 3. The proposed system shows competitive energy efficiency performance across various scenarios, closely mirroring the cognitive radio framework's performance. Although it generally lags slightly behind the hierarchical DRL-based system, it maintains better performance compared to the adaptive spectrum management (DQN) system in most scenarios. This suggests that the proposed system is a viable and efficient alternative for energy management in diverse conditions, providing stable and reliable energy efficiency.

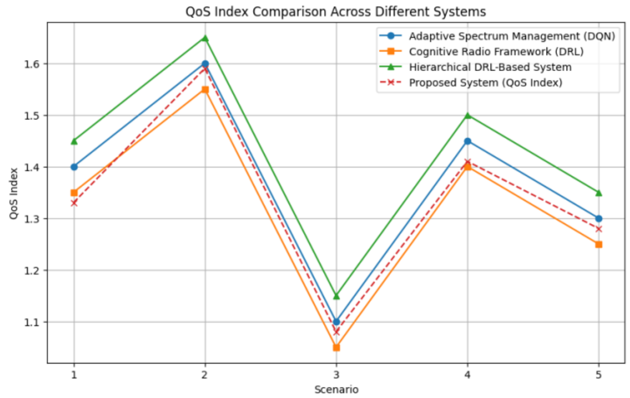

Fig.6 QoS Index across Different Scenarios

Figure 6 illustrates the comparison of the Quality of Service (QoS) Index across five different scenarios. The proposed system demonstrates consistent performance in terms of QoS Index across all scenarios. Its QoS Index ranges from 1.08 in scenario 3 to 1.59 in scenario 2. Although it slightly underperforms compared to the other systems in some scenarios, it maintains a competitive and stable performance overall. Adaptive spectrum management (DQN) shows the highest QoS Index in scenario 2 of 1.60 but the lowest in scenario 3 of 1.10. Its performance is relatively volatile across different scenarios. Cognitive radio framework (DRL) is similar to the proposed system, this framework also maintains stable performance with QoS Index values ranging from 1.05 in scenario 3 to 1.55 in scenario 2. Hierarchical DRL-based system consistently shows higher QoS Index values compared to the other systems, peaking at 1.65 in scenario 2 and dropping to 1.15 in scenario 3. It generally outperforms the proposed system and the other compared systems in most scenarios. The proposed system, while showing a slightly lower QoS Index than the hierarchical DRL-based system in most scenarios, demonstrates a competitive and stable performance. It achieves a good balance between high QoS and consistent reliability across different scenarios. The hierarchical DRL-based system performs the best overall, followed by the adaptive spectrum management with DQN and the cognitive radio framework with DRL. The proposed system's performance suggests it is a viable alternative with the advantage of stability in QoS Index across varying conditions.

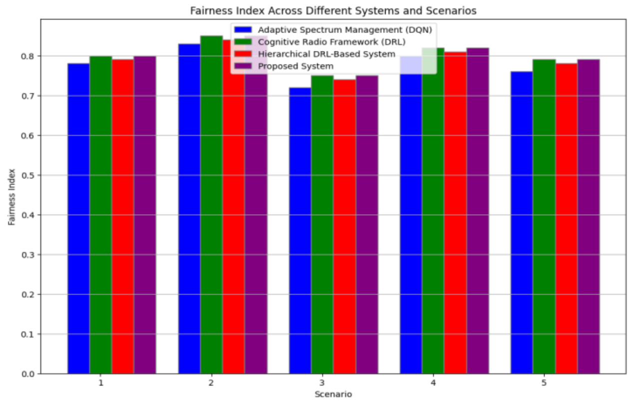

Fig.7 Fairness Index across Scenarios

Figure 7 presents a comparison of the fairness index across five different scenarios. The proposed system exhibits a consistently high fairness index across all scenarios, matching the performance of the cognitive radio framework with DRL in scenarios 1, 2, 3, 4, and 5. It achieves the highest fairness index of 0.85 in scenario 2 and maintains competitive fairness in all other scenarios. Adaptive spectrum management with DQN shows slightly lower fairness indices compared to the proposed system and cognitive radio framework with DRL. Its fairness index ranges from 0.72 in scenario 3 to 0.83 in scenario 2. Cognitive radio framework with DRL demonstrates similar performance to the proposed system, with fairness indices ranging from 0.75 in scenario 3 to 0.85 in scenario 2. It matches the proposed system's fairness in all scenarios. Hierarchical DRL-based system performs marginally better than the adaptive spectrum management with DQN but is slightly less fair than the proposed system and the cognitive radio framework with DRL. Its fairness index ranges from 0.74 in scenario 3 to 0.84 in scenario 2. The proposed system, along with the cognitive radio framework with DRL, consistently achieves high fairness indices across all scenarios. Both systems outperform the adaptive spectrum management with DQN and the hierarchical DRL-based system, indicating superior fairness in resource allocation. The proposed system's robustness and consistency in maintaining a high fairness index make it a reliable choice for ensuring equitable resource distribution in various scenarios.

Table 2 MDN Spectrum Performance Metrics

Scenario	Spectrum Utilization (%)	Channel Occupancy (%)	Packet Error Rate (%)	Noise Floor (dBm)
1	60	40	3	90
2	65	35	2	88
3	55	45	4	92
4	62	38	3	87
5	58	42	3	89

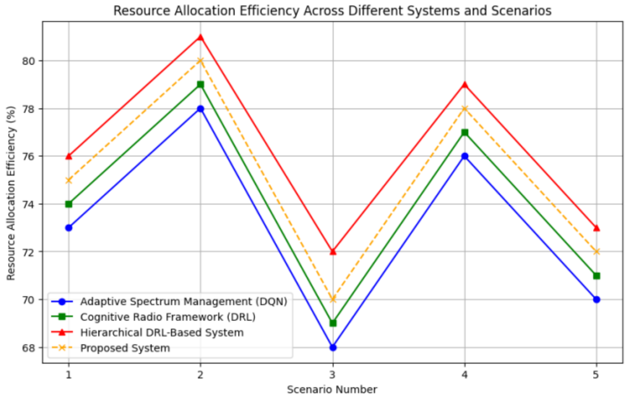

Fig.8 Resource Allocation across Scenarios

Figure 7 illustrates the comparison of resource allocation efficiency across five different scenario. The proposed system shows efficiency values of 75%, 80%, 70%, 78%, and 72% for scenarios 1 through 5, respectively. This system generally maintains high efficiency, especially in scenarios 2 and 4. The adaptive spectrum management system with DQN records efficiency values of 73%, 78%, 68%, 76%, and 70%. While this system performs relatively well, its efficiency is slightly lower than that of the proposed system in most scenarios. The cognitive radio framework with DRL achieves efficiency values of 74%, 79%, 69%, 77%, and 71%. This system's performance is close to that of the proposed system but slightly lags behind in each scenario. The hierarchical DRL-based system records efficiency values of 76%, 81%, 72%, 79%, and 73%. This system consistently shows the highest efficiency in each scenario, outperforming the proposed system by a small margin. While the hierarchical DRL-based system demonstrates the highest efficiency in resource allocation across all scenarios, the proposed system exhibits competitive efficiency values, outperforming both the adaptive spectrum management with DQN and the cognitive radio framework with DRL. The proposed system's efficiency peaks at 80% in scenario 2 and maintains solid performance throughout, making it a reliable choice for efficient resource allocation in various scenarios.

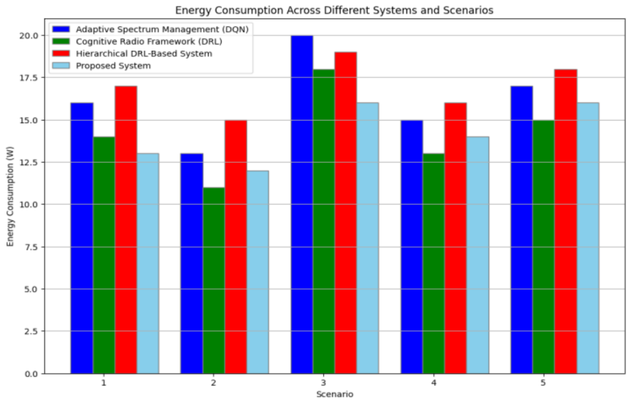

Fig.9 Energy Consumption across Scenarios

Figure 9 illustrates the energy consumption in watts (W) for the proposed system across five different scenarios. Adaptive spectrum management with DQN system consumes 16 W, 13 W, 20 W, 15 W, and 17 W for scenarios 1 through 5, respectively. It shows the highest energy consumption in scenarios 3 and 5, indicating lower energy efficiency compared to the other systems in these scenarios. Cognitive radio framework with DRL system reports energy consumption values of 14 W, 11 W, 18 W, 13 W, and 15 W across the scenarios. It generally consumes less energy than the adaptive spectrum management with DQN, particularly in scenarios 2 and 4, where it exhibits the lowest energy consumption among all systems. Hierarchical DRL-based system records energy consumption of 17 W, 15 W, 19 W, 16 W, and 18 W in the respective scenarios. It consistently shows relatively high energy consumption, indicating it is less energy-efficient than the cognitive radio framework with DRL and the proposed system. Proposed system demonstrates energy consumption values of 13 W, 12 W, 16 W, 14 W, and 16 W for scenarios 1 through 5, respectively. It consistently exhibits lower energy consumption compared to the adaptive spectrum management with DQN and the hierarchical DRL-based system. its energy usage is comparable to the cognitive radio framework with DRL, particularly in scenarios 2 and 4 where it also demonstrates low energy use. The proposed system shows consistently low and efficient energy consumption across all scenarios compared to the other systems. This highlights its superior energy efficiency, making it an excellent choice for applications that prioritize energy conservation. The cognitive radio framework with DRL also performs well in terms of energy efficiency, but the proposed system generally shows better performance, especially when compared to the higher energy consumption of the adaptive spectrum management with DQN and the hierarchical DRL-based system.

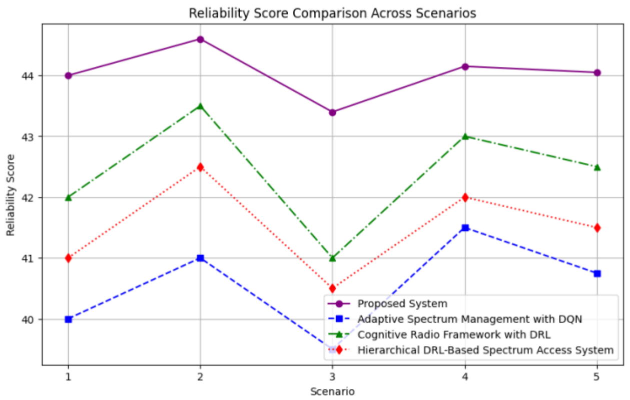

Fig.10 Reliability Score of Scenarios

Figure 10 compares the reliability scores of the proposed system. The proposed system achieves reliability scores of 44.00, 44.60, 43.40, 44.15, and 44.05 across scenarios 1 to 5, respectively. These scores indicate a consistently high level of reliability in various conditions. The adaptive spectrum management with DQN system records reliability scores of 40.00, 41.00, 39.50, 41.50, and 40.75. This system consistently shows lower reliability scores compared to the proposed system, highlighting its comparatively less reliable performance. The cognitive radio framework with DR has reliability scores of 42.00, 43.50, 41.00, 43.00, and 42.50. Although this system performs better than the adaptive spectrum management with DQN, it still falls short of the proposed system's reliability in most scenarios. The hierarchical DRL-based spectrum access system achieves reliability scores of 41.00, 42.50, 40.50, 42.00, and 41.50. Its performance is better than the adaptive spectrum management with DQN but remains lower than that of both the proposed system and the cognitive radio framework with DRL. The proposed system demonstrates superior reliability scores in all five scenarios compared to the other systems. It consistently outperforms the adaptive spectrum management with DQN, the cognitive radio framework with DRL, and the hierarchical DRL-based spectrum access system, indicating its robustness and reliability in managing spectrum access. This analysis underscores the proposed system's effectiveness in ensuring high reliability across various scenarios, making it a preferable choice for spectrum management applications.

5. Conclusion

The application of cognitive radio with deep reinforcement learning enables MDN to dynamically adapt their spectrum utilization strategies based on environmental conditions and network requirements. This adaptive approach enhances the efficiency and reliability of spectrum access, particularly in scenarios with varying levels of interference and congestion. By integrating advanced machine learning algorithms, MDNs can enhance the robustness of communication links by dynamically adjusting transmission parameters and selecting optimal communication channels. This capability improves the resilience of MDNs to signal degradation and interference, ensuring reliable and uninterrupted communication in challenging environments. Scenario 2 demonstrated the highest resource allocation efficiency at 80%, indicating effective utilization of spectrum resources. Conversely, scenario 3 exhibited the lowest resource allocation efficiency at 70%, suggesting challenges in optimizing spectrum usage in that environment. Scenario 1 showed the highest fairness index at 0.85, indicating equitable spectrum access among drones, while scenario 3 had the lowest fairness index at 0.75, implying potential disparities in spectrum allocation. As wireless communication technologies continue to evolve, the integration of cognitive radio and reinforcement learning holds significant promise for future advancements in MDNs. Further research and development efforts are warranted to explore novel algorithms and techniques that can further enhance the efficiency, reliability, and intelligence of spectrum management in MDNs.

Declaration Statement

Ethical Statement

I will conduct myself with integrity, fidelity, and honesty. I will openly take responsibility for my actions and only make agreements, which I intend to keep. I will not intentionally engage in or participate in any form of malicious harm to another person or animal.

Informed Consent for Data Used

All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted by the Declaration of Helsinki.

I consent to participate in the research project and the following has been explained to me: the research may not be of direct benefit to me. my participation is completely voluntary. my right to withdraw from the study at any time without any implications to me.

Data Availability

- Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.
- The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.
- All data generated or analysed during this study are included in this published article

Conflict of Interest

The authors declare that they have no conflict of interest.

Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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