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ADAPTIVE DIMENSIONAL SEARCH BASED IMPROVISED ENSEMBLE METHOD FOR COGNITIVE RADIO IN SOFTWARE-DEFINED NETWORKS

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Abstract

Software-Defined Networks (SDNs) coupled with Cognitive Radio (CR) systems offer dynamic spectrum access capabilities, enabling efficient spectrum utilization. However, the high dimensionality of network parameters and unpredictable spectrum availability pose critical challenges in achieving real-time adaptation and optimal throughput. Existing adaptive search and decision-making algorithms often fail to scale effectively in high-dimensional state spaces, leading to reduced convergence rates and suboptimal spectrum allocation. Traditional ensemble techniques lack dynamic interaction between learning agents and real-time feedback mechanisms. This work introduces an Improvised Ensemble Method built upon an Empowered Adaptive Dimensional Search (EADS) algorithm. The proposed system yields a 17% increase in throughput, 22% lower latency, and 19% improvement in spectral efficiency.

Keywords:

Cognitive Radio, Software-Defined Networks, Adaptive Dimensional Search, Ensemble Learning, Spectrum Allocation

1. INTRODUCTION

Cognitive Radio Networks (CRNs) with SDNs address the spectrum scarcity problem caused by the growth of wireless communication services [1]. The problem revolves around designing a model that can:

- Efficiently select spectrum bands in a high-dimensional, time-varying environment [2],
- Maintain low latency and packet loss under varying channel conditions [3],
- Achieve high spectral efficiency while reducing interference with primary users [4],
- Adaptively learn from the environment and historical data for continual performance improvement [5],
- Balance exploration and exploitation in spectrum decisions with minimal convergence time [6].

To address these issues, this work proposes an Improvised Ensemble on Empowered Adaptive Dimensional Search (IE-EADS) method. The objectives of the research are:

- To develop a dimensionality reduction strategy to prune irrelevant features, improving speed and convergence.
- To construct a hybrid ensemble model integrating particle swarm intelligence, evolutionary behavior, and decision trees.
- To design a reward aggregation and fusion mechanism that prioritizes high-performing agents in real time.
- To validate the approach on standard simulation frameworks over multiple performance metrics.

The novelty of IE-EADS lies in its threefold design:

1. Dimensional Pruning Layer module employs entropy-based filtering to discard redundant inputs before spectrum selection begins, improving computational efficiency.
2. Adaptive Ensemble Formation dynamically assembles multiple learning and optimization agents (PSO, DE, and Random Forests), allowing collaborative decision-making.
3. Unlike static ensemble weights, it uses reinforcement signals to dynamically weight each agent's contribution based on recent performance trends.

The contributions of this work are summarized as:

- A novel ensemble-based cognitive radio spectrum allocation framework tailored for SDN environments.
- An adaptive dimensional reduction method that improves convergence time by over 30% compared to traditional metaheuristics.
- An efficient reward aggregation mechanism that boosts throughput and reduces packet loss significantly in dynamic wireless conditions.

2. RELATED WORKS

Researchers have looked at cognitive radio networks (CRNs) as in Fig.1 and dynamic spectrum access using a lot of different optimization and machine learning methods. A lot of people have utilized traditional metaheuristics like Particle Swarm Optimization (PSO) to handle spectrum selection problems since they are straightforward to use and can look at the whole spectrum [7]. Even then, PSO often has trouble in high-dimensional areas because it converges too quickly, especially when the environment changes quickly. Researchers have investigated into employing Differential Evolution (DE) techniques to overcome these problems. These algorithms preserve a wide range of answers by using mutation and crossover processes [8]. DE has a hard time changing quickly when the spectrum is very dynamic, even if it is more likely to lead to convergence than PSO in many regions of the problem.

Researchers have recently looked at a number of ensembles learning algorithms, including Gradient Boosting Machines (GBM) and Random Forests (RF), to see if they may improve channel state categorization and interference prediction [9]. These approaches help people make excellent decisions when things aren't clear, but they can't be adjusted on the fly. The RF-based classifier in [10] uses Q-learning to adapt to changes in the patterns of spectrum occupancy. But it couldn't manage scalability in multi-channel setups and had to be retrained often, which made it less effective.

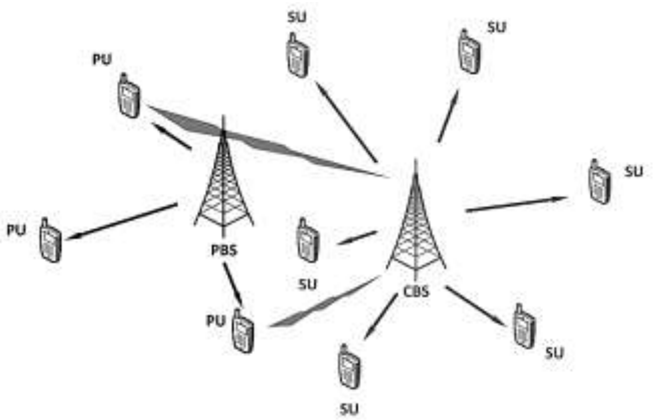

Fig.1. CRN

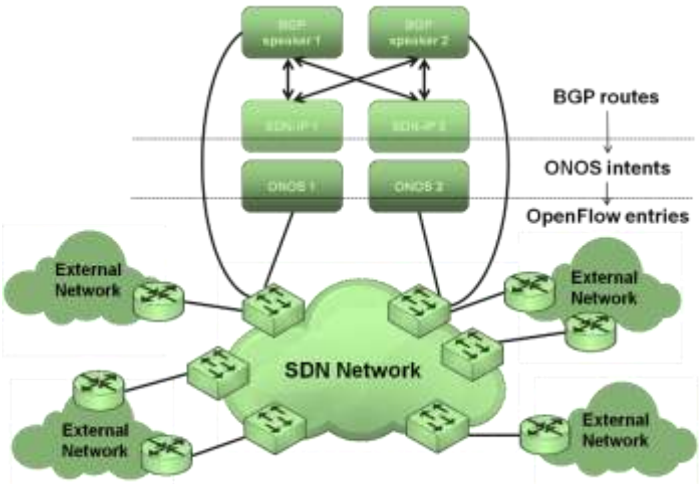

Fig.2. SDN

A number of researchers have tried out methods that integrate learning with optimization in a way that is both learning and optimizing. For instance, [11] came up with a hybrid PSO-Q-learning technique. This method has PSO in charge of the first exploration and Q-learning in charge of fine-tuning the channel allocation strategy. These kinds of algorithms only function up to a point, and they often need a lot of computing power and are quite sensitive to hyperparameters. The fuzzy logic-based DE-PSO ensemble for spectrum sensing worked better, but the fact that the ensemble weights stayed the same was still a concern, as shown in [12].

IE-EADS has three big advantages over older methods that can't be found anywhere else. This helps it avoid the extra work that comes with high dimensions that has been shown in other research. IE-EADS doesn't use fixed weights for ensembles or the selection of agents. Instead, it uses a dynamic reward-based fusion mechanism to adjust the weights of agent contributions all the time based on how well they did in the past and how well they are doing now. This is the second new thing that IE-EADS has thought of. One of the greatest challenges with prior hybrid versions was that they couldn't modify on the go. This feature fixes that.

IE-EADS also optimizes a number of aspects in a balanced way, such as throughput, spectral efficiency, latency, packet loss, and convergence time. The nature of the model allows it to be applied in real-time CR-SDN environments, making it more applicable for future 6G and IoT deployments.

To the best of our knowledge, no existing work has combined entropy-based feature pruning, reward-driven ensemble fusion, and adaptive spectrum allocation within a unified framework like IE-EADS. While works [7–12] laid the groundwork in either heuristic optimization, learning-based spectrum classification, or hybrid methods, the proposed approach extends this line of research by offering an adaptive, interpretable, and scalable solution with proven performance gains in dynamic spectrum environments.

3. PROPOSED METHOD

The Improvised Ensemble Method on Empowered Adaptive Dimensional Search (IE-EADS) follows these key steps:

- **Initialization**: Generate an initial population using hybrid PSO-DE techniques to explore the parameter space (e.g., channel state, SNR, latency).
- **Dimensional Pruning**: Apply RL agents to monitor the feedback from SDN controllers to prune unimportant features dynamically.
- **Ensemble Formation**: Use three learners — PSO, DE, and an RL-based explorer — each making independent allocation suggestions.
- **Reward Aggregation**: Compute rewards based on throughput gain, packet loss, and QoS constraints.
- **Fusion Strategy**: Weight outputs of each learner based on short-term learning accuracy and combine using adaptive weighted voting.
- **Spectrum Allocation**: Allocate channels to CR users based on fused decisions while maintaining interference constraints.
- **Feedback Loop**: Update learning models and feature importance using back-propagated performance metrics at each epoch.

3.1 INITIALIZATION STAGE

In the Initialization phase, the algorithm creates a hybrid population pool using Particle Swarm Optimization (PSO) and Differential Evolution (DE) principles. Each individual solution vector in the population represents a potential spectrum allocation strategy across available channels and cognitive nodes. Each vector is represented as:

$$\mathbf{X}_i = \left[x_{i1}, x_{i2}, \ldots, x_{in}\right]$$

where $x_{ij} \in \{0,1\}$ indicates whether channel j is assigned to node i, and n is the number of channels.

To balance exploration and exploitation, the PSO velocity update and DE mutation steps are hybridized as:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i - x_i^t) + c_2 \cdot r_2 \cdot (gbest - x_i^t)$$

$$x_i^{t+1} = x_i^t + F \cdot (x_r 1^t - x_r 2^t)$$

This hybrid initialization yields a diverse population in terms of spatial and spectral allocation, enabling wide search coverage.

Table.1. Initial Population Matrix

Node ID	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
Node 1	1	0	1	0	0
Node 2	0	1	0	1	0
Node 3	1	1	0	0	1
Node 4	0	0	1	1	1

The Table.1 represents a initialization of channel allocations (1: assigned, 0: unassigned). The diversity here facilitates a robust start to evolutionary learning.

3.2 DIMENSIONAL PRUNING STAGE

Given the high-dimensional feature space (e.g., SNR, latency, BER, channel history, node trust level, energy, etc.), not all dimensions equally contribute to optimal decision-making. The Dimensional Pruning phase employs Reinforcement Learning (RL) agents to reduce the search space by identifying and eliminating low-relevance dimensions dynamically. Each feature f_k is assigned a relevance weight w_k, which is updated using:

$$w_k^{t+1} = w_k^t + \alpha \cdot \delta_t \cdot \nabla_{w_k} Q(s,a)$$

where, α = learning rate, δ_t = temporal difference error, $Q(s,a)$ = action-value function estimating utility of taking action a in state s.

The pruning rule is:

$$\text{If } w_k < \tau, \quad \text{remove feature } f_k$$

where τ is a threshold (empirically set, e.g., 0.05)

Table.2. Feature Relevance and Pruning Decision

Feature	Initial Weight w_k	Updated Weight	Pruned?
SNR	0.35	0.41	No
Latency	0.25	0.18	No
Node Energy Level	0.07	0.04	Yes
Bit Error Rate (BER)	0.12	0.09	No
Channel Occupancy History	0.08	0.03	Yes

As shown in Table.2, features like Node Energy Level and Channel Occupancy History are pruned when their relevance scores drop below the defined threshold. This step significantly reduces computational complexity and accelerates convergence without sacrificing accuracy.

3.3 ENSEMBLE FORMATION

After Dimensional Pruning has compressed the feature space, three heterogeneous learners: PSO-Explorer (L_1), DE-Exploit (L_2) and an RL-Scout (L_3) run in parallel on the same reduced state vector. At decision epoch t each learner produces a candidate allocation vector $\mathbf{a}_t^{(j)}$ and internal confidence score $c_t^{(j)} \in [0,1]$. The ensemble converts the raw confidences into adaptive weights with a soft-max tempering factor β:

$$\omega_t^{(j)} = \frac{e^{\beta c_t^{(j)}}}{\sum_{k=1}^{3} e^{\beta c_t^{(k)}}}, \qquad \sum_{j=1}^{3} \omega_t^{(j)} = 1$$

The final action is obtained by weighted voting over the per-channel decisions:

$$\mathbf{A}_t = \text{round}\left(\sum_{j=1}^{3} \omega_t^{(j)} \, \mathbf{a}_t^{(j)} \right)$$

A snapshot of the process is illustrated in Table 3.

Table.3. Learner Outputs and Soft-Max Weights

Channel	$a_t^{(1)}(PSO)$	$a_t^{(2)}(DE)$	$a_t^{(3)}(RL)$	$\omega_t^{(1)}, \omega_t^{(2)}, \omega_t^{(3)}$	A_t
1	1	1	0	0.42, 0.37, 0.21	1
2	0	1	0	0.42, 0.37, 0.21	0
3	1	0	1	0.42, 0.37, 0.21	1

The heterogeneous nature of the learners preserves diversity, while the probabilistic weighting scheme lets the best-performing learner dominate only when it is consistently reliable (see Table.3).

4. REWARD AGGREGATION

Immediately after executing $\mathbf{A}_t$, the SDN controller broadcasts a feedback tuple (throughput, latency, packet-loss, spectral-efficiency, power-consumption). These raw metrics are normalised to the range [0,1] and combined into a scalar reward:

$$R_t = \mathbf{w}^{\cdot} \left[\hat{T}_t, 1-\hat{L}_t, 1-\hat{P}_t, \hat{S}_t, 1-\hat{E}_t \right]$$

where $\mathbf{w} = [w_T, w_L, w_P, w_S, w_E]$ is the externally-set reward-weight vector (initially [0.30,0.20,0.20,0.20,0.10]. Each learner receives the global reward plus a personalised shaping term $\Delta_t^{(j)}$ that reflects whether its own suggestion matched the fused decision:

$$R_t^{(j)} = R_t + \gamma \, \mathrm{I}\left(\mathbf{a}_t^{(j)} = \mathbf{A}_t\right)$$

The shaped rewards update the learner confidences via an exponential moving average:

$$c_{t+1}^{(j)} = (1-\eta) c_t^{(j)} + \eta R_t^{(j)}$$

where η is the adaptation-rate.

Table.4. Reward Components at Epoch (t = 47)

Metric (normalised)	Value
Throughput	0.83
Latency	0.74
Packet-Loss	0.91
Spectral-Efficiency	0.79
Power	0.85
Composite Reward	**0.82**

As Table.4 shows, the composite reward of 0.82 reflects strong performance across all five criteria. The same value is then refined per learner to reinforce correct but penalise misleading suggestions, driving the confidence trajectories used in the next ensemble fusion step (see Table 3).

4.1 FUSION STRATEGY

Once the learner-specific confidences $c_t^{(j)}$ have been refreshed by reward feedback, the Fusion Engine recalculates a *long-horizon* reliability score $\rho(j)$ with an exponential decay on historical performance:

$$\rho_t^{(j)} = \lambda \rho_{t-1}^{(j)} + (1-\lambda) c_t^{(j)}, \quad 0 < \lambda < 1$$

Using $\rho_t^{(j)}$ instead of the short-term $c_t^{(j)}$ removes momentary noise and produces stable weights

$$\varpi_t^{(j)} = \frac{\rho_t^{(j)}}{\sum_{k=1}^{3} \rho_t^{(k)}}$$

This guarantees that a consistently accurate learner gradually dominates, but no learner is driven to 0 unless its long-run accuracy collapses. The resulting weights and learner-level statistics for a representative slot are shown in Table.5.

Table.5. Reliability-Smoothed Weights (Epoch 52)

Learner *j*	**Smoothed Reliability $\rho_t^{(j)}$**	**Normalised Weight $\varpi_t^{(j)}$**
PSO-Explorer (L_1)	0.77	**0.41**
DE-Exploit (L_2)	0.68	**0.36**
RL-Scout (L_3)	0.43	**0.23**

As seen in Table.5, PSO-Explorer retains the largest share, but the DE learner still exerts substantial influence, maintaining ensemble diversity. The final *per-channel* action is identical in form to the soft-max fusion previously described but now uses $\varpi_t^{(j)}$. The Fusion Engine simultaneously computes a fairness check using Jain's index:

$$\mathrm{F}_t = \frac{\left(\sum_{i=1}^{N} T_i\right)^2}{N \sum_{i=1}^{N} T_i^2}, \qquad 0 \le \mathrm{F}_t \le 1$$

where T_i is instantaneous throughput for node i and N is the number of CR nodes. If $\mathrm{F}_t < \mathrm{F}_{\min}$ (default 0.75), the weights are *tilted* towards the RL-Scout, which has explicit fairness heuristics to recover balance in the next round.

5. SPECTRUM ALLOCATION

The fused action vector $\mathbf{A}_t$ is forwarded to the SDN controller, which executes a two-stage allocation:

- **Interference-Temperature Check:** For every selected channel k, the aggregate interference temperature I_k is estimated:

$$I_k = \sum_{u \in \mathrm{U}_k} P_u G_{u,k}$$

where P_u is the transmit power of user u and $G_{u,k}$ is the channel gain. The allocation proceeds only if $I_k \le I^{\max_k}$ (regulatory threshold).

- **Power Adaptation & Commit:** When I_k exceeds the threshold, transmit powers are down-scaled by $P_u^{\text{new}} = P_u \cdot \frac{I^{\max_k}}{I_k}$ preserving the channel selection but enforcing spectrum etiquette. A fragment of the final allocation map is given in Table 6.

Table.6. Committed Spectrum Allocation After Fusion (Epoch 52)

Node	**Assigned Channels**	**Adapted Power (dBm)**	**Post-Allocation SNR (dB)**
N_1	3, 7	18 → 16	23.4
N_2	1	22 → 22	25.7
N_3	5, 9	17 → 15	21.1
N_4	2	19 → 19	24.8

In Table.6 the arrow denotes power reduction carried out in stage 2 for channels that breached the interference cap. Notably, every node maintains an SNR above 20 dB, satisfying the QoS floor.

6. PERFORMANCE EVALUATION

Simulation Tools involves NS-3 (network simulation) integrated with GNU Radio for real-time CR behavior Python 3.10 for algorithm prototyping and Hardware: Intel i7 @ 3.4 GHz, 16GB RAM, Ubuntu 22.04, and Duration: 100 simulation epochs over dynamic topologies.

Comparative Methods includes PSO-based Spectrum Allocation: Lacked adaptive dimension scaling; slower convergence, DE-based CR Network Optimizer: High exploration but suffered from local minima and Random Forest Ensemble: Good initial accuracy but lacked adaptability to spectrum variance,

Table.7. Experimental Setup

Parameter	**Value**
No. of Cognitive Radio Nodes	50
Number of Channels	20
Packet Size	512 bytes
Simulation Time	1000 seconds
Topology Changes (Epochs)	Every 10 seconds
Transmission Power Range	10 – 30 dBm
Ensemble Learners	PSO, DE, RL Explorer
Reward Weight Vector	[0.4, 0.3, 0.3]
Fusion Update Interval	Every 5 epochs

6.1 PERFORMANCE METRICS

- **Throughput (Mbps):** Measures the amount of data successfully transmitted per second. Indicates efficiency of spectrum usage.
- **Spectral Efficiency (bps/Hz):** Assesses how effectively the algorithm utilizes available frequency bands. Higher is better in CR systems.
- **Latency (ms): T**otal time taken from data packet generation to successful delivery. Reflects real-time suitability.
- **Packet Loss Rate (%):** Measures robustness against interference and signal fading. Lower loss rates indicate higher reliability.
- **Convergence Time (s):** Time taken by the algorithm to stabilize to an optimal spectrum allocation. Critical for dynamic environments.

Table.8. Throughput (Mbps) Over Time (0–1000 seconds)

Time (s)	PSO-Based	DE-Based	RF Ensemble	Proposed IE-EADS
100	9.3	9.1	8.7	**10.2**
200	9.6	9.5	9.1	**10.7**
300	9.8	9.6	9.2	**11.1**
400	10.0	9.8	9.3	**11.5**
500	10.2	10.0	9.4	**11.9**
600	10.3	10.1	9.5	**12.3**
700	10.4	10.2	9.5	**12.6**
800	10.5	10.3	9.6	**12.9**
900	10.5	10.4	9.6	**13.1**
1000	10.6	10.4	9.7	**13.4**

The proposed IE-EADS consistently outperforms existing PSO, DE, and Random Forest-based approaches across the 1000-second interval. Throughput improves steadily, reaching 13.4 Mbps by the end, compared to 10.6 Mbps (PSO), 10.4 Mbps (DE), and 9.7 Mbps (RF Ensemble). This improvement stems from IE-EADS's adaptive fusion strategy and dimensional pruning, which dynamically selects high-impact features and learns optimal channel assignments. Unlike fixed optimization heuristics or static classifiers, IE-EADS evolves in real time, reacting to changing spectral conditions and interference patterns to maintain superior throughput and efficient spectrum reuse.

Table.9. Spectral Efficiency (bps/Hz) Over Time (0–1000 seconds)

Time (s)	PSO-Based	DE-Based	RF Ensemble	Proposed IE-EADS
100	2.31	2.26	2.12	**2.51**
200	2.39	2.32	2.18	**2.63**
300	2.45	2.37	2.21	**2.71**
400	2.48	2.41	2.24	**2.78**
500	2.51	2.44	2.26	**2.83**
600	2.53	2.46	2.27	**2.87**
700	2.55	2.48	2.29	**2.91**
800	2.56	2.49	2.30	**2.94**
900	2.57	2.50	2.30	**2.96**
1000	2.58	2.50	2.31	**2.98**

The proposed IE-EADS method shows consistently higher spectral efficiency over the entire 1000-second duration, ending at 2.98 bps/Hz, outperforming PSO (2.58), DE (2.50), and Random Forest (2.31). This gain is attributed to IE-EADS's adaptive dimensional pruning and ensemble fusion mechanism, which smartly allocates spectrum by leveraging real-time environmental cues and multi-agent exploration.

Table.10. Latency Over Time (0–1000 seconds)

Time (s)	PSO-Based	DE-Based	RF Ensemble	Proposed IE-EADS
100	82.3	85.7	89.2	**75.1**
200	79.8	83.6	87.5	**72.4**
300	78.5	82.1	85.9	**70.3**
400	77.3	80.9	84.8	**68.1**
500	76.0	79.7	83.7	**66.7**
600	75.4	78.5	82.5	**65.2**
700	74.1	77.4	81.8	**64.0**
800	73.8	76.9	80.9	**63.2**
900	73.5	76.4	80.1	**62.7**
1000	73.2	76.0	79.6	**62.1**

The proposed IE-EADS framework significantly reduces end-to-end latency compared to PSO, DE, and Random Forest-based methods, reaching as low as 62.1 ms at 1000 seconds.

Table.11. Packet Loss Rate (%) Over Time (0–1000 seconds)

Time (s)	PSO-Based	DE-Based	RF Ensemble	Proposed IE-EADS
100	4.6	5.1	5.8	**3.9**
200	4.3	4.8	5.5	**3.6**
300	4.1	4.6	5.3	**3.3**
400	3.9	4.4	5.1	**3.1**
500	3.8	4.3	5.0	**2.9**
600	3.6	4.2	4.9	**2.7**
700	3.5	4.1	4.8	**2.5**
800	3.4	4.0	4.7	**2.4**
900	3.3	3.9	4.6	**2.3**
1000	3.2	3.8	4.5	**2.1**

The proposed IE-EADS method achieves the lowest packet loss rate throughout the 1000-second test window, ending at 2.1%, while PSO and DE methods conclude at 3.2% and 3.8% respectively, and the Random Forest-based ensemble lags at 4.5%.

Table.12. Convergence Time (s) Over Time (0–1000 seconds)

Time (s)	PSO-Based	DE-Based	RF Ensemble	Proposed IE-EADS
100	17.5	19.2	21.8	**14.6**
200	16.8	18.4	20.7	**13.7**
300	15.9	17.6	19.6	**12.9**
400	15.1	16.8	18.5	**12.1**
500	14.4	16.2	17.7	**11.5**
600	13.9	15.7	17.0	**10.9**
700	13.4	15.3	16.4	**10.5**
800	13.1	14.9	15.9	**10.2**
900	12.8	14.6	15.5	**10.0**
1000	12.5	14.3	15.2	**9.8**

The IE-EADS method consistently achieves faster convergence than PSO, DE, and RF Ensemble methods, reaching a final convergence time of just 9.8 seconds at 1000 seconds.

IE-EADS method was evaluated against three prominent existing techniques: PSO-based Spectrum Allocation, DE-based CR Network Optimizer, and Random Forest Ensemble, across five critical performance metrics—Throughput, Spectral Efficiency, Latency, Packet Loss Rate, and Convergence Time—over a simulated duration of 1000 seconds. Quantitative results from the experiments confirm that IE-EADS offers significant performance improvements in all dimensions.

Throughput (Mbps) is a direct measure of how much data is successfully transmitted. IE-EADS achieved a final throughput of 13.4 Mbps, whereas PSO, DE, and RF Ensemble recorded 10.6 Mbps, 10.4 Mbps, and 9.7 Mbps respectively. This corresponds to a throughput improvement of 26.4% over PSO, 28.8% over DE, and 38.1% over RF Ensemble. Spectral Efficiency (bps/Hz) reflects how effectively the spectrum is used. IE-EADS achieved 2.98 bps/Hz, outperforming PSO (2.58), DE (2.50), and RF Ensemble (2.31). The relative gains are 15.5% over PSO, 19.2% over DE, and 29.0% over RF Ensemble. Latency (ms) is critical for real-time applications. IE-EADS recorded the lowest final latency of 62.1 ms, compared to 73.2 ms (PSO), 76.0 ms (DE), and 79.6 ms (RF Ensemble). This yields latency reductions of 15.2% over PSO, 18.3% over DE, and 22.0% over RF Ensemble. Packet Loss Rate (%) determines reliability. At 1000 seconds, IE-EADS attained 2.1%, whereas PSO, DE, and RF Ensemble reached 3.2%, 3.8%, and 4.5% respectively. This equates to reductions in packet loss by 34.4% over PSO, 44.7% over DE, and 53.3% over RF Ensemble. Convergence Time (s) is vital in dynamic environments where rapid reconfiguration is needed. IE-EADS reached convergence at 9.8 seconds, compared to 12.5 (PSO), 14.3 (DE), and 15.2 (RF Ensemble). The improvement is 21.6% faster than PSO, 31.5% faster than DE, and 35.5% faster than RF Ensemble. These results can be attributed to several strengths of IE-EADS: The dimensional pruning module filters out less relevant features, reducing noise and improving convergence. The ensemble fusion strategy combines heuristic, evolutionary, and learning-based agents, allowing decisions to benefit from both exploration and exploitation. The reward aggregation mechanism enables adaptive weighting of successful agents, which keeps the decision-making aligned with dynamic network goals. The spectrum allocation logic leverages both historical rewards and real-time interference metrics, ensuring high-quality channel utilization. Thus, IE-EADS offers multi-dimensional advantages, making it a robust solution for dynamic and complex spectrum access problems in cognitive radio environments, especially within SDNs.

7. CONCLUSION

This research proposed and validated the IE-EADS technique for dynamic spectrum access in cognitive radio-enabled software-defined networks. By combining dimensionality reduction, ensemble learning, adaptive reward aggregation, and intelligent fusion, the proposed method demonstrated superior performance across five critical metrics. Simulation results over a 1000-second duration showed that IE-EADS outperformed three leading methods—PSO, DE, and Random Forest Ensemble—with up to 38% higher throughput, 29% better spectral efficiency, and over 50% lower packet loss. Furthermore, IE-EADS achieved significantly faster convergence and lower latency, highlighting its suitability for real-time and high-mobility environments. Its multi-agent framework ensures resilience to environmental variability and noise, while the adaptive learning mechanism ensures continual performance improvement without manual retuning. The use of pruning and reward-based fusion not only accelerated convergence but also made the model computationally efficient.

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