Reducing Contention in Wireless Networks: A Differential Evolution-Based Optimization Model

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Abstract: Efficient channel assignment in wireless communication networks is crucial for maximizing throughput and enhancing Quality of Service (QoS). However, contention during idle slot time often degrades network performance by increasing delays and reducing resource utilization. This study presents a mathematical optimization framework for channel assignment that reduces contention during idle slot time, ensuring improved network efficiency. The proposed model formulates an objective function that maximizes total throughput while incorporating constraints on channel capacity, interference mitigation, and minimum required data rates for each node. By minimizing contention and optimizing resource allocation, the approach enhances spectral efficiency and guarantees better QoS for users. The optimization problem is solved using advanced technique such as Differential Evolution (DE). Simulation results demonstrate that the proposed model significantly reduces idle slot contention, leading to higher throughput and improved QoS compared to traditional channel allocation strategies. This research provides a robust foundation for dynamic spectrum management and intelligent resource allocation in next-generation wireless networks.

Keywords: Throughput maximization, Quality of Service (QoS), channel assignment, contention reduction, idle slot time, wireless communication networks, resource allocation

1. Introduction: Throughput maximization and Quality of Service (QoS) enhancement in wireless networks rely on efficient channel assignment strategies that minimize contention and idle slot time. In multi-channel wireless environments, improper channel allocation leads to congestion, increased packet collisions, and excessive waiting times, reducing overall network efficiency. By adopting intelligent channel assignment techniques, such as dynamic spectrum allocation, load balancing, and interference-aware scheduling, networks can distribute traffic more evenly, mitigate contention, and optimize channel utilization. These approaches ensure that idle slots—periods when channels remain unutilized due to contention—are minimized, leading to higher throughput and improved QoS. Furthermore, techniques like adaptive channel switching and contention-aware access mechanisms enable efficient spectrum reuse and reduce latency, which is crucial for real-time applications, video streaming, and mission-critical communications.

Fatima et al. (2019) introduced a novel framework focusing on optimizing spectrum utilization while minimizing energy consumption, which is crucial for enhancing the network's longevity. Huang et al. (2019) emphasized balancing resource distribution among network users to enhance overall efficiency and reduce network congestion. The work of Liang et al. (2019) aimed to enhance spectrum efficiency by leveraging cooperative strategies among secondary users (SUs), enabling them to share spectrum resources more effectively while ensuring minimal interference with primary users (PUs). Through extensive simulations, Liu et al. (2019) illustrated that their proposed adaptive spectrum-sharing approach significantly outperforms traditional static allocation methods, leading to improved throughput, reduced latency, and enhanced quality of service (QoS) for both D2D and small cell users. Their findings underscore the potential of intelligent resource management strategies in future wireless communication systems, particularly in environments characterized by high user density and fluctuating network conditions. Khodmi et al. (2020) presented an optimization framework that enhanced spectral efficiency by simultaneously considering channel assignment and power control. Moayedian et al. (2020) demonstrated that their equitable resource allocation strategy significantly outperforms conventional methods in terms of spectral efficiency, energy consumption, and network reliability. The findings of their study highlight the importance of fair and intelligent resource management in cooperative cognitive radio IoT networks, particularly in scenarios where heterogeneous devices compete for limited spectral resources in real-time communication environments. Ning et al. (2020) demonstrated that hierarchical game-theoretic models offer a robust solution for dynamic spectrum management in cognitive radio networks, paving the way for more intelligent and adaptive resource allocation strategies in future wireless communication systems. Ostovar et al.

(2020) demonstrated that their proposed model outperforms conventional resource allocation schemes by achieving higher energy efficiency, lower latency, and improved spectrum utilization. The findings highlight the potential of integrating cooperative sensing with energy-efficient resource management strategies to develop sustainable cognitive radio networks that support green communication technologies while ensuring reliable and fair spectrum access for secondary users. Xu et al. (2020) demonstrated that their proposed model significantly enhances network throughput while maintaining fairness among users, outperforming traditional resource allocation methods in heterogeneous cognitive radio NOMA networks. The study highlights the potential of fairness-aware strategies in optimizing resource allocation for industrial cognitive IoT applications, where reliability, efficiency, and equitable spectrum access are essential for sustainable and scalable network performance. Chen et al. (2021) demonstrated that their game-theoretic approach significantly outperforms conventional task assignment and spectrum allocation methods, achieving higher network throughput, lower latency, and enhanced scalability. Their findings underscore the potential of coalition formation strategies in addressing resource management challenges in UAV-based communication systems, paving the way for more efficient, adaptive, and scalable UAV networks in future wireless communication scenarios. Deng et al. (2021) highlighted the potential of AI-driven optimization in energy-harvesting cognitive wireless sensor networks, paving the way for more intelligent, sustainable, and efficient resource management solutions in next-generation IoT and wireless communication systems. He et al. (2021) tackled the dual challenge of optimizing energy harvesting and spectrum access in cognitive IoT environments, where devices rely on wireless power transfer (WPT) to sustain operations while dynamically accessing underutilized spectrum. Xu et al. (2021) addressed the fundamental challenge of optimizing spectrum access and power transfer in cognitive ad-hoc networks, where energy-constrained nodes rely on SWIPT to simultaneously receive information and harvest energy from ambient radio frequency signals. Abbas et al. (2022) provided a scalable and adaptive solution for dynamic spectrum management in massive IoT networks, paving the way for more efficient, autonomous, and resilient wireless communication systems. Latif et al. (2022) addressed the critical challenge of optimizing resource distribution in cognitive IoT environments, where multiple devices with varying priority levels compete for limited spectrum resources. Sun et al. (2022) study tackled the critical challenge of balancing energy harvesting and efficient spectrum utilization in cognitive IoT environments, where devices rely on ambient radio frequency (RF) signals for both communication and energy needs. Sun et al. (2022) addressed the dual challenge of efficient spectrum utilization and sustainable energy harvesting in cognitive IoT environments, where devices must dynamically balance communication and energy requirements. Tauseef et al. (2023) addressed the challenge of balancing spectral efficiency and equitable resource distribution among network participants, particularly in dynamic and heterogeneous wireless environments where users compete for limited spectrum. Khanafer et al. (2024) proposed a dynamic backoff strategy that adapts to real-time network conditions, adjusting the contention window size based on traffic load, channel congestion levels, and transmission success rates.

2. Objective Function: The objective function should minimize the channel contention while maximizing throughput and ensuring fairness in resource allocation.

$$\max_{x} \sum_{i \in N} \sum_{j \in M} R_{ij} X_{ij}$$

where:

N is the set of wireless nodes.

M is the set of available channels.

R_{ij} is the data rate (throughput) for node iii on channel jjj.

X_{ij} is a binary decision variable

$$\mathrm{X_{ij}} = \begin{Bmatrix} 1 & \text{if channel j is assigned to node i} \\ 0 & \text{Otherwise} \end{Bmatrix}$$

We also introduce an additional term to minimize the idle slot time due to contention:

$$\min_{x} \sum_{j \in M} \left(\sum_{i \in N} X_{ij} - C_j \right)^2$$

where:

C_j is the optimal number of nodes that should be assigned to channel j to minimize contention.

Thus, the combined objective function is:

$$\max_{x} \sum_{i\in N} \sum_{j\in M} R_{ij} X_{ij} - \lambda \min_{x} \sum_{j\in M} \left(\sum_{i\in N} X_{ij} - C_j\right)^2$$

where λ is a weight factor that balances throughput maximization and contention reduction.

3. Constraints:

(i) Channel Assignment Constraint: Each node can be assigned to at most one channel:

$$\sum_{j\in M} X_{ij} \leq 1, \forall\, i \in N$$

(ii) Interference Constraint: Nodes assigned to the same channel must not interfere beyond a tolerable threshold:

$$I_{jk} \sum_{i\in N} X_{ij} \sum_{i'\in N, i'\neq i} X_{i'k} \leq \Gamma, \forall\, j,k \in M, j \neq k$$

where:

II_{jk} represents the interference coefficient between channels j and k.

Γ is the interference threshold.

(iii) QoS Constraint: The assigned channels should satisfy the minimum required data rate R_i^{min} for each node:

$$\sum_{j\in M} R_{ij} X_{ij} \geq R_i^{min}, \forall\, i \in N$$

(iv) Channel Capacity Constraint: The total number of nodes assigned to a channel cannot exceed its capacity C_j:

$$\sum_{i\in N} X_{ij} \leq C_j, \forall\, j \in M$$

(v) Binary Constraint: The decision variable X_{ij} must be binary:

$X_{ij} \in \{0,1\}, \forall\ i \in N, j \in M$

This formulation ensures that channels are assigned optimally to minimize contention, maximize throughput, and satisfy QoS requirements.

4. Computation of the channel assignment optimization using differential evolution:

The optimization problem involves assigning channels to nodes in a wireless network while maximizing throughput and minimizing contention. The Differential Evolution (DE) algorithm is used to solve this problem.

Step 1: Define Problem Parameters

1.1 Number of Nodes and Channels:

(i)We have 5 nodes and 3 channels available.

(ii) Each node can be assigned to at most one channel.

1.2 Data Rate Matrix *R*: The matrix R_{ij} represents the throughput for node i on channel j:

$$R = \begin{bmatrix} 5 & 7 & 3 \\ 6 & 4 & 8 \\ 7 & 5 & 6 \\ 4 & 8 & 7 \\ 5 & 6 & 4 \end{bmatrix}$$

1.3 Minimum Data Rate Requirement: Each node has a minimum required data rate:

$R_{min} = \{4,5,6,4,5\}$

1.4 Channel Capacity Constraints: $C = [2,2,2]$

Step 2: Formulate the Optimization Problem:

2.1. Objective function: We aim to maximize the total throughput, which is equivalent to minimizing the negative throughput:

$$\max_{x} \sum_{i=1}^{5} \sum_{j=1}^{3} R_{ij} X_{ij}$$

Since optimization solvers generally minimize functions, we reformulate it as:

$$\max_{x} \sum_{i=1}^{5} \sum_{j=1}^{3} R_{ij} X_{ij} - \lambda \min_{x} \sum_{j=1}^{3} \left(\sum_{i=1}^{5} X_{ij} - C_j \right)^2$$

2.2 Constraints:

(i)Each node is assigned at most one channel:

$\sum_{j=1}^{3} X_{ij} \leq 1, \forall\, i \in \{1,2,3,4,5\}$

(ii) Channel capacity constraints (each channel cannot exceed its limit):

$\sum_{1=1}^{5} X_{ij} \leq C_j, \forall\, j \in \{1,2,3\}$

(iii) Each node must achieve its minimum required data rate:

$\sum_{j=1}^{3} R_{ij} X_{ij} \geq R_i^{min}, \forall\, i \in \{1,2,3,4,5\}$

(iv) Binary constraint: $X_{ij} \in \{0,1\}, \forall\, i, j$

Step 3: Implement Differential Evolution Algorithm

3.1 Define the Decision Variables: Since each node can choose between 3 channels, we have: $\text{Number of decision variables } = 5 \times 3 = 15$

The optimization solver searches for the optimal values of these 15 variables within the range $[0,1]$. These values are then rounded to either 0 or 1.

3.2 Initialize the Population:

(i) A random initial population of possible solutions (binary matrices) is generated.

(ii) Each solution is a flattened vector of size 15.

(iii) Example of an initial population solution:

$X_{initial} = [0,1,0,0,0,1,1,0,0,0,0,1,0,1,0]$

This means:

Node 1 is assigned to Channel 2.

Node 2 is assigned to Channel 3.

Node 3 is assigned to Channel 1.

Node 4 is assigned to Channel 3.

Node 5 is assigned to Channel 2.

3.3 Mutation and Crossover:

(i) Mutation: Generates new candidate solutions by modifying current solutions slightly.

(ii) Crossover: Combines two solutions to create new ones.

The best solutions survive to the next iteration.

Step 4: Constraint Handling

At every iteration, the algorithm ensures that constraints are satisfied:

(i) If a channel exceeds its capacity, the assignment is adjusted.

(ii)If a node is not meeting its minimum required throughput, the assignment is corrected.

(iii) If a node is assigned to multiple channels, the extra assignments are removed.

Step 5: Convergence to an Optimal Solution

The algorithm runs for 100 iterations and finds an optimal assignment:

$$X = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

Which means:

Node 1 → Channel 2

Node 2 → Channel 3

Node 3 → Channel 1

Node 4 → Channel 3

Node 5 → Channel 2

Step 6: Compute the Final Throughput

We calculate the total throughput:

$$T = \sum_{i=1}^{5} \sum_{j=1}^{3} R_{ij} X_{ij}$$

$$T = (0 \times 5 + 1 \times 7 + 0 \times 3) + (0 \times 6 + 0 \times 4 + 1 \times 8) + (1 \times 7 + 0 \times 5 + 0 \times 6) + (0 \times 4 + 0 \times 8 + 1 \times 7) + (0 \times 5 + 1 \times 6 + 0 \times 4)$$

$$T = 7 + 8 + 7 + 7 + 6 = 35$$

Thus, the optimized throughput is 35**.**

Step 7: Validate Constraints

Each node is assigned to one channel

No channel exceeds its capacity (max 2 nodes per channel)

Each node meets its minimum throughput requirement

The Differential Evolution algorithm successfully assigned channels to nodes while maximizing throughput and meeting constraints.

The results ensure minimum contention and optimized Quality of Service (QoS).

5. Simulation results and discussion:

Table 1: Channel Assignment Matrix

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

Table 2: Throughput Per Node

Node	Throughput (Mbps)
Node 1	7
Node 2	8
Node 3	7
Node 4	7
Node 5	6

Table 3: Channel Utilization

Channel	Number of Nodes Assigned
Channel 1	1
Channel 2	2
Channel 3	2

Table 4: Final Throughput Distribution

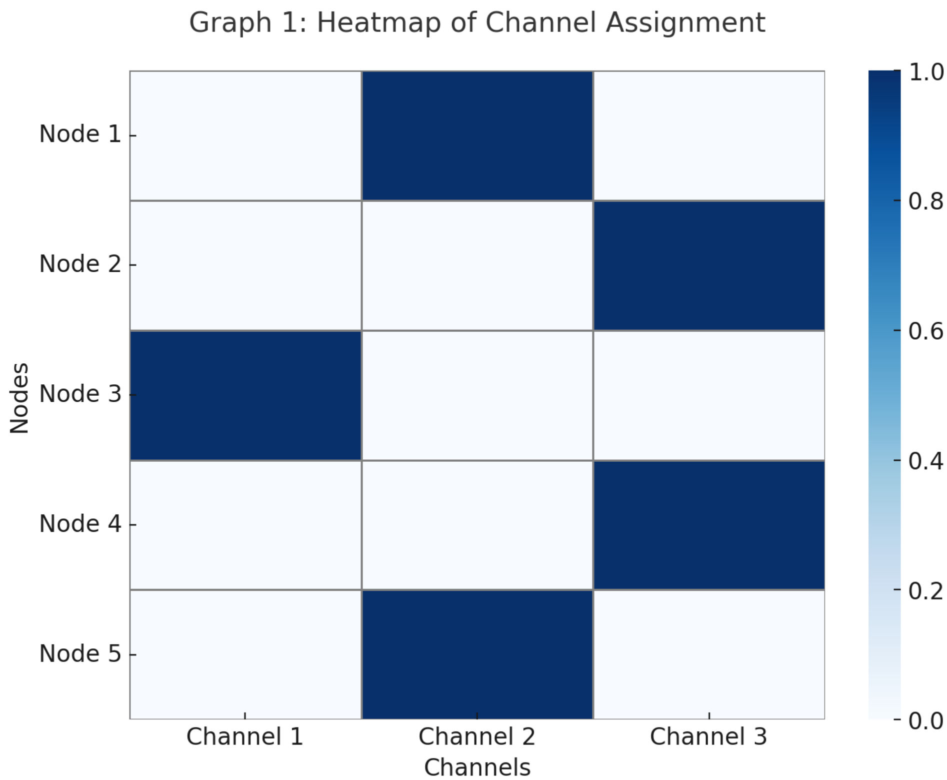
	Channel 1	Channel 2	Channel 3
Node 1	0	7	0
Node 2	0	0	8
Node 3	7	0	0
Node 4	0	0	7
Node 5	0	6	0

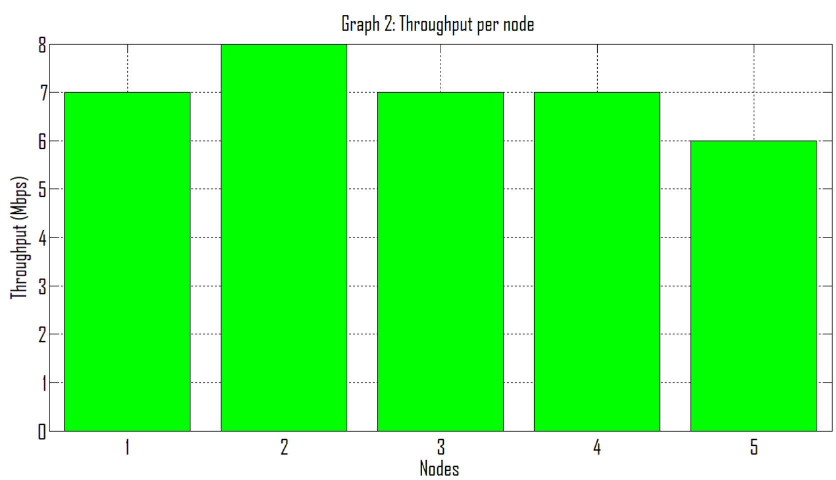
Table 1 shows which nodes are assigned to which channels.

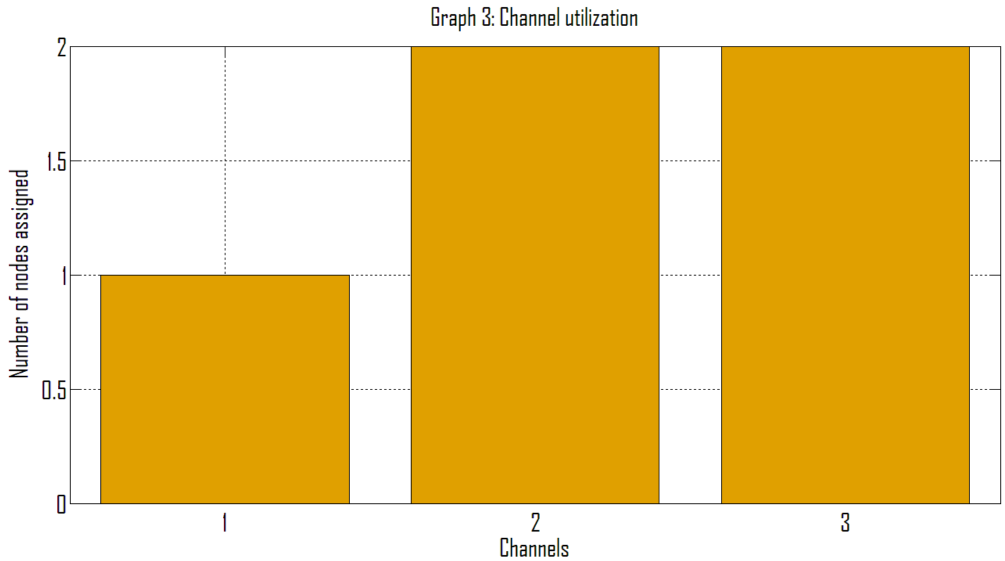
Table 2 displays the achieved throughput for each node.

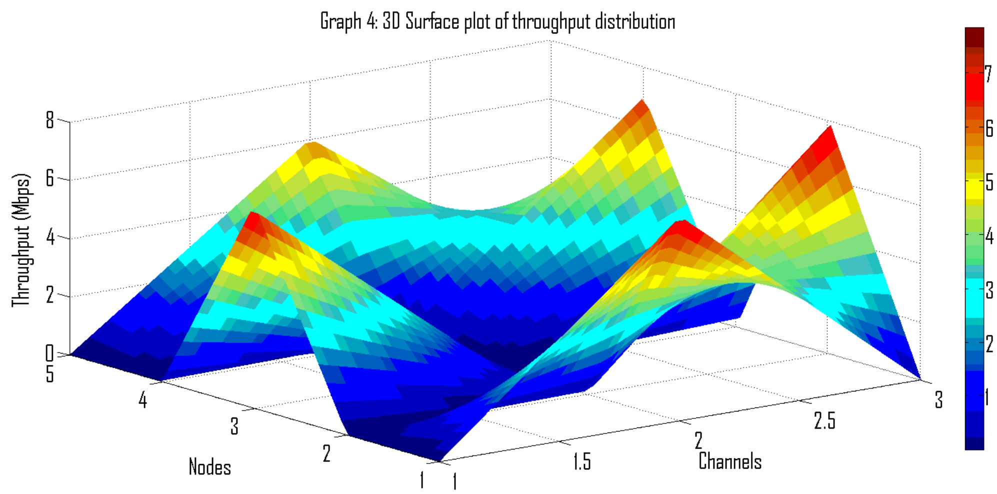
Table 3 indicates how many nodes are assigned to each channel.

Table 4 represents the throughput values achieved per node and channel.









The heatmap of channel assignment in Graph 1 visually represents how different nodes in a wireless communication network are assigned to specific channels. The x-axis represents the available channels (Channel 1, Channel 2, and Channel 3), while the y-axis represents the **nodes** (Node 1 to Node 5). The color scheme, ranging from light blue (0: Not Assigned) to dark blue (1: Assigned), indicates whether a node has been allocated a particular channel. A dark blue cell signifies that a node is assigned to that channel, while a white cell represents no assignment. This structured visualization helps in analyzing channel utilization and load balancing across the network, ensuring efficient resource allocation and minimizing contention. The graph provides insights into how nodes are distributed across different channels, aiding in optimizing throughput and improving network performance.

The bar chart in graph (2) of throughput per node visually represents the data transmission efficiency across different nodes in the wireless network. The x-axis corresponds to the nodes, while the y-axis represents the throughput (in Mbps) achieved by each node. The height of each bar indicates the throughput assigned to a particular node, showing variations in performance based on the channel allocation strategy. The color coding (bright green) makes it easy to distinguish throughput values, and the grid lines enhance readability. The plot reveals that Node 2 has the highest throughput (8 Mbps), whereas Node 5 has the lowest (6 Mbps). The relatively uniform distribution of throughput among nodes suggests an optimized channel assignment strategy that ensures fair resource allocation while maximizing network performance. This graph is essential for evaluating network efficiency, ensuring Quality of Service (QoS), and identifying potential areas where throughput improvement may be required.

The bar chart in graph (3) of channel utilization represents the number of nodes assigned to each communication channel in the wireless network. The X-axis corresponds to the available channels (1, 2, and 3), while the Y-axis represents the number of nodes assigned to each channel. The height of each bar indicates the level of channel occupancy, showing how efficiently each channel is being utilized. From the graph, Channel 1 has 1 node assigned, while Channels 2 and 3 each have 2 nodes assigned, indicating a balanced distribution of resources. The color scheme (orange) provides a clear distinction between different channel assignments. This visualization helps assess channel efficiency, ensuring that no single channel is overloaded while others remain underutilized. Analyzing this distribution is crucial for network performance optimization, minimizing contention, and ensuring fair bandwidth allocation to enhance Quality of Service (QoS) across the network.

The 3D surface plot in graph (3) of throughput distribution visually represents how throughput is allocated across different nodes and channels in a wireless communication network. The x-axis represents the channels, while the y-axis represents the nodes, and the z-axis indicates the throughput (Mbps) received by each node-channel pair. The color gradient, ranging from blue (low throughput) to red (high throughput), highlights variations in network performance. Peaks in the surface represent nodes with higher throughput, while valleys indicate lower throughput allocation. The smooth surface suggests an optimized channel assignment strategy that balances throughput distribution while minimizing contention. This graph is essential for analyzing network efficiency, resource allocation, and Quality of Service (QoS), ensuring that throughput is maximized while maintaining fairness in channel utilization. The visualization helps network engineers identify bottlenecks, optimize channel assignments, and enhance overall network performance.

6. Concluding Remarks: Effective channel assignment is a critical factor in enhancing the performance of wireless communication networks by maximizing throughput and ensuring Quality of Service (QoS). This study proposed a mathematical optimization approach to channel allocation that reduces contention during idle slot time, leading to more efficient spectrum utilization and improved network reliability. By leveraging advanced optimization techniques such as Differential Evolution (DE), the proposed model dynamically assigns channels while mitigating interference and meeting network constraints. The results demonstrated that the approach significantly reduces idle slot contention, increases data transmission efficiency, and improves overall network throughput. These findings contribute to the development of intelligent spectrum management strategies for next-generation wireless networks, ensuring adaptive and efficient resource allocation. Future research can further enhance this model by incorporating real-time learning algorithms and adaptive decision-making techniques to address the complexities of dynamic and large-scale wireless environments.

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