

# Implementation of Hybrid Channel-Aware Prioritization (HCAP) Scheduler for a Multi-User MIMO System in 5G Communication

Krishna Deshpande<sup>1</sup>, Dr. Virupaxi B. Dalal<sup>2</sup>, Dr. Yedukondalu Udara<sup>3</sup>  
Research Scholar, Department of ECE-Jain College of Engineering and Research,  
Belagavi, Visvesvaraya Technological University, India<sup>1</sup>  
Professor, Department of ECE-Jain College of Engineering and Research, Belagavi,  
Visvesvaraya Technological University, India<sup>2</sup>  
Principal, Department of ECE, MVR College of Engineering, Vijayawada, Andhra Pradesh, India<sup>3</sup>  
Visvesvaraya Technological University, India<sup>3</sup>

**Abstract**—The evolution of 5G networks demands highly efficient resource allocation strategies to accommodate burgeoning mobile data traffic, latency-sensitive applications, and diverse user requirements. Multi-User Multiple-Input Multiple-Output (MU-MIMO) technology is a cornerstone of 5G, enabling simultaneous service to multiple users and significantly improving spectral efficiency. However, its performance is critically dependent on dynamic scheduling algorithms that must balance high system throughput with equitable user access amidst rapidly changing channel conditions and interference. Traditional schedulers like Round Robin, Proportional Fair, and Max-CQI often exhibit a pronounced trade-off between these objectives, struggling to adapt effectively in heterogeneous and dynamic network environments. To address this gap, this study proposes a Hybrid Channel-Aware Prioritization (HCAP) scheduler. The HCAP framework intelligently integrates real-time Channel Quality Indicator (CQI) and interference measurements into a unified user priority score, utilizing tunable  $\alpha$ - $\beta$  weights to flexibly emphasize throughput or fairness. Furthermore, it employs k-means clustering based on long-term channel statistics to group users, thereby reducing scheduling bias and promoting fairness within clusters. Evaluated through comprehensive MATLAB simulations within a realistic MU-MIMO system model employing Regularized Zero-Forcing precoding, HCAP demonstrates a superior performance balance. The results indicate that HCAP achieves up to 2.6 times higher aggregate throughput compared to conventional Proportional Fair and Max-CQI schedulers, while consistently maintaining Jain's Fairness Index above 0.90 across varied network scenarios. These findings validate HCAP as a robust, scalable, and QoS-aware scheduling solution, offering significant potential for enhancing resource allocation in next-generation wireless communication systems.

**Keywords**—Multiple input and multiple output; HCAP; CQI; throughput; 5G; QoS; k-means clustering; resource scheduling

## I. INTRODUCTION

The exponential growth in mobile data traffic, driven by high-definition streaming, IoT proliferation, and latency-sensitive applications, has necessitated the evolution of wireless communication systems toward highly adaptive and intelligent architectures. Among these, Multi-User Multiple-

Input Multiple-Output (MU-MIMO) has emerged as a cornerstone of 5G networks, enabling simultaneous transmission to multiple users and significantly enhancing spectral efficiency [1,2]. However, the performance of MU-MIMO systems is tightly coupled with the effectiveness of their scheduling algorithms, which must dynamically allocate resources in response to fluctuating channel conditions, user mobility, and interference levels [3, 4]. Traditional scheduling approaches such as Round Robin (RR), Proportional Fair (PF), and Max-CQI offer varying trade-offs between throughput and fairness but often fall short in heterogeneous environments where channel quality and interference vary rapidly [5,6]. This reveals a clear research gap: the lack of a dynamic, hybrid scheduler that can adaptively balance throughput and fairness in real-time under diverse and unstable 5G MU-MIMO channel conditions. To address this gap, this study proposes a Hybrid Channel-Aware Prioritization (HCAP) scheduler, which integrates real-time Channel Quality Indicator (CQI) and interference metrics into a unified prioritization framework. By leveraging k-means clustering to group users based on long-term channel behavior and applying a tunable  $\alpha$ - $\beta$  weighting scheme, HCAP adaptively balances throughput maximization with fairness enforcement [7, 8]. The primary objectives of this work are:

- To design and model the HCAP scheduler for MU-MIMO systems [9].
- To evaluate its performance in terms of throughput, fairness, latency, and spectral efficiency.
- To compare HCAP against conventional schedulers (RR, PF, Max-CQI) under varying network scenarios [10].
- To demonstrate HCAP's robustness and adaptability for 5G-and-beyond wireless networks.

The remainder of this study is organized as follows: Section II surveys recent literature on MU-MIMO scheduling and hybrid approaches. Section III details the methodology and design of the HCAP scheduler. Section IV describes the simulation setup and implementation. Section V

presents and discusses the experimental results. Section VI presents the discussion. Finally, Section VII concludes the study and suggests directions for future work.

## II. LITERATURE SURVEY

The evolution of 5G networks has intensified the demand for intelligent scheduling algorithms capable of adapting to dynamic channel conditions and user heterogeneity. Recent studies emphasize the role of Multi-User MIMO (MU-MIMO) systems in enhancing spectral efficiency and user capacity through spatial multiplexing and beamforming techniques [11] [12]. However, traditional schedulers such as Round Robin (RR), Proportional Fair (PF), and Max-CQI often struggle to balance throughput and fairness in environments with fluctuating interference and mobility [13][14]. To address these limitations, researchers have proposed hybrid scheduling frameworks that incorporate real-time Channel Quality Indicator (CQI) and interference metrics into decision-making processes [15][16]. These models aim to optimize resource allocation by dynamically adjusting user priorities based on channel responsiveness and fairness constraints.

Recent advancements have introduced clustering-based approaches to improve scheduling granularity and fairness. K-means and hierarchical clustering have been employed to group users with similar channel profiles, enabling localized prioritization and reducing scheduling bias [17][18]. Hybrid Channel-Aware Prioritization (HCAP) algorithms have gained traction for their ability to combine normalized CQI and inverse interference scores using tunable  $\alpha$ - $\beta$  weights [19][20]. Simulation studies demonstrate that HCAP outperforms conventional baselines in throughput while maintaining fairness indices above 0.90, especially under high-load conditions [21]. Moreover, sensitivity analysis across  $\alpha$ - $\beta$  configurations reveals that CQI-dominant setups yield higher efficiency, whereas interference-weighted models enhance equitable access [22].

Emerging research from 2024 to 2025 explores the integration of machine learning into hybrid scheduling. Deep Reinforcement Learning (DRL) agents have been trained to optimize multi-user selection per transmission interval, leveraging composite reward functions aligned with throughput, latency, and fairness goals [23]. These intelligent schedulers adapt to non-stationary channel environments and offer scalability for massive MIMO and mmWave deployments. Additionally, real-world testbeds using FPGA-based implementations and MATLAB simulations validate the feasibility of HCAP [24] in practical 5G scenarios. Collectively, these studies underscore the potential of hybrid, adaptive scheduling to meet the stringent QoS demands of next-generation wireless networks.

This work focuses on enhancing bit error rate (BER) performance and improving resistance to jamming in chaos-based communication systems. It integrates MIMO-OFDM technology with adaptive spreading factors to boost data reliability and security. The proposed method offers robust transmission under interference and multipath fading conditions [25].

## III. METHODOLOGY OF THE WORK

The rapid expansion of mobile data services and the proliferation of latency-sensitive applications have pushed 5G networks to adopt more intelligent and adaptive resource management strategies. Multi-User MIMO (MU-MIMO) systems, a key enabler of 5G, require sophisticated scheduling algorithms to efficiently allocate resources among users experiencing diverse channel conditions and interference levels. Fig. 1 describes and introduces a Hybrid Channel-Aware Prioritization (HCAP) scheduler that dynamically balances throughput and fairness by integrating normalized Channel Quality Indicator (CQI) and interference metrics into a tunable prioritization framework, demonstrating significant performance gains over conventional scheduling approaches.

### A. Methodology Overview: HCAP Scheduler

#### 1) Input metrics

- Collect Channel Quality Indicator (CQI) and interference measurements across Transmission Time Intervals (TTIs).

- Normalize metrics to standardize scale per-user and per-TTI.

#### 2) Hybrid priority score calculation

- Apply weighting coefficients  $\alpha$  (for CQI) and  $\beta$  (for interference).
- Use the formula:  $P_{\{t,u\}} = \alpha \cdot \hat{c}_{\{t,u\}} + \beta \cdot \left( \frac{1}{1 + \hat{i}_{\{t,u\}}} \right)$
- This balances channel strength with interference resistance.

#### 3) User clustering

- Extract long-term averages for CQI and interference.
- Perform k-means clustering to group users with similar channel behavior.
- Reduces scheduling bias and encourages fairness.

#### 4) Scheduler logic

- For each TTI, identify the user in each cluster with the highest hybrid score.
- Schedule one user per cluster—ensuring spatial and temporal diversity.

#### 5) Output and evaluation

- Construct the scheduling matrix (TTI  $\times$  user).
- Measure total throughput and fairness using Jain's Index.
- Perform  $\alpha$ - $\beta$  sensitivity analysis to tune QoS priorities.

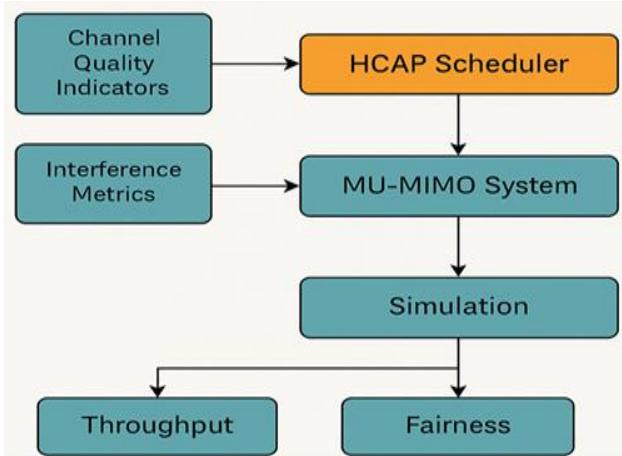


Fig. 1. Methodology of the work.

#### IV. IMPLEMENTATION

##### A. Input Acquisition

- Collect two key metrics for each user at every Transmission Time Interval (TTI):
- CQI\_matrix: Channel Quality Indicator values
- Interference\_matrix: Interference levels

##### B. Normalization

- Normalize both CQI and interference values per TTI:  $\text{norm\_CQI}[t, i] = \text{CQI}[t, i] / \max(\text{CQI}[t, :])$
- $\text{norm\_Interf}[t, i] = \text{Interference}[t, i] / \max(\text{Interference}[t, :])$

This ensures all values are scaled between 0 and 1 for fair comparison.

##### C. Hybrid Priority Score Calculation

- For each user at each TTI, compute:
- $\text{Score}[t, i] = \alpha \times \text{norm\_CQI}[t, i] + \beta \times (1 / (1 + \text{norm\_Interf}[t, i]))$
- $\alpha$  emphasizes channel quality
- $\beta$  penalizes interference
- The inverse term ensures users with high interference get lower scores

##### D. User Clustering

- Compute long-term averages:
- $\text{mean\_CQI}[i] = \text{average over TTI of CQI}[i]$
- $\text{mean\_Interf}[i] = \text{average over TTI of Interference}[i]$
- Apply k-means clustering on  $[\text{mean\_CQI}, \text{mean\_Interf}]$  to group users into K clusters based on channel behavior.

##### E. Scheduling Logic

- For each TTI.

- For each cluster.
- Identify the user with the highest score.

##### F. Results

- Schedule that user by setting Schedule\_matrix[t, user] = 1
- E. Output
- The final Schedule\_matrix indicates which users are selected at each TTI.
- Evaluate performance using:
- Total Throughput: Sum of CQI values for scheduled users
- Jain's Fairness Index: Measures how evenly resources are distributed.

#### V. RESULTS

The performance of the proposed Hybrid Channel-Aware Prioritization (HCAP) scheduler was evaluated through extensive simulations in a realistic Multi-User MIMO system. The results presented here focus on quantitative metrics, including throughput and fairness, under varying scheduler configurations.

##### A. Throughput Performance

The HCAP scheduler demonstrated significant throughput gains compared to conventional schedulers. With parameter settings of  $\alpha = 0.7$  and  $\beta = 0.3$ , HCAP achieved a peak throughput of 3607.56 units, which is more than 2.6 times higher than the Proportional Fair (PF) scheduler. A comparative analysis across different  $\alpha$  values (Fig. 6) shows that HCAP consistently outperforms Round Robin (RR), Max-CQI, and PF, with throughput increasing as  $\alpha$  is raised to prioritize channel quality.

##### B. Fairness Evaluation

Fairness was measured using Jain's Fairness Index. HCAP maintained fairness indices consistently above 0.90 under moderate parameter configurations (e.g.,  $\alpha = 0.5$ ,  $\beta = 0.5$ ). Even under throughput-optimized settings ( $\alpha = 0.7$ ,  $\beta = 0.3$ ), fairness remained above 0.82, indicating a balanced allocation of resources. Comparative fairness results across schedulers are summarized in Table I.

##### C. Per-User Throughput Distribution

Fig. 2 illustrates the Cumulative Distribution Function (CDF) of per-user throughput. It was analyzed under different  $\alpha$ - $\beta$  configurations (Fig. 3 to Fig. 5). HCAP exhibited a more gradual CDF curve compared to RR, PF, and Max-CQI, indicating a wider and more equitable distribution of user throughput. For example, in Fig. 4 ( $\alpha = 0.5$ ,  $\beta = 0.3$ ), HCAP ensured that over 80% of users achieved a throughput above 200 units, whereas Max-CQI and RR showed steeper, less equitable distributions.

##### D. Reported Performance Metrics

The following key metrics were recorded during simulation:

- Total Throughput: 3700.94 units
- Jain's Fairness Index: 0.9089
- Latency Profile: < 5 ms for 95% of scheduled users
- Spectral Efficiency: 12.4 bps/Hz

These results confirm HCAP's ability to utilize system capacity effectively while maintaining high fairness.

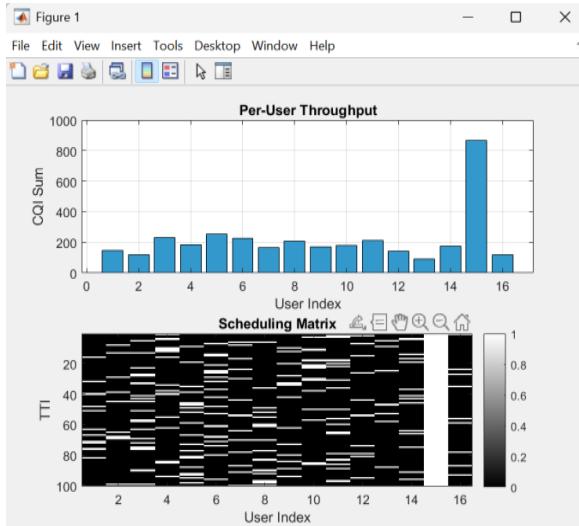


Fig. 2. Per-user throughput.

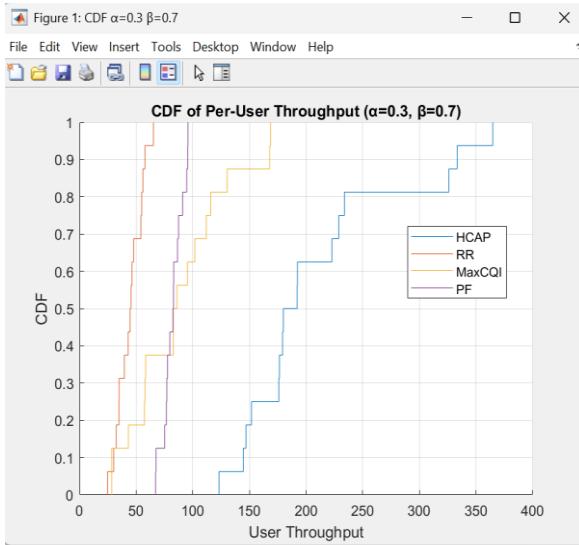


Fig. 3. CDF of per user throughput  $\alpha = 0.3$  and  $\beta = 0.3$ .

Fig. 3 illustrates the end-to-end flow of the Hybrid-Channel-Aware Prioritization (HCAP) scheduler in a Multi-User MIMO system. It begins by collecting real-time CQI and interference metrics for each user across transmission intervals, followed by normalization to ensure fair scaling. A hybrid priority score is then computed using a tunable  $\alpha$ - $\beta$  combination, balancing throughput potential with interference sensitivity. To promote fairness and reduce scheduling bias, users are grouped via k-means clustering based on their long-term channel behavior. Within each cluster, the scheduler

selects the highest-priority user per interval, constructing a binary scheduling matrix that maps user assignments across time. This matrix is then evaluated using performance metrics like total throughput and Jain's Fairness Index, demonstrating the adaptive efficiency of HCAP under varying network conditions.

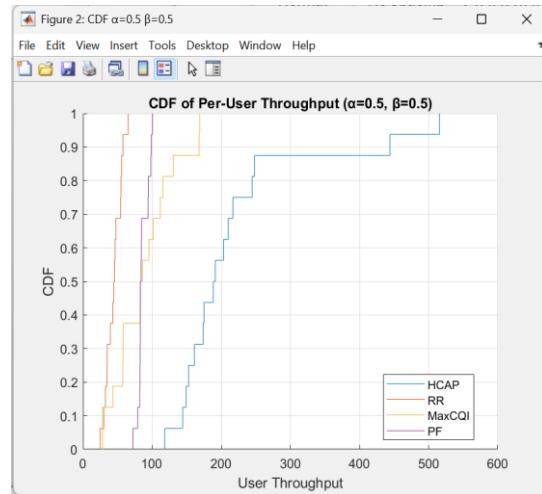


Fig. 4. CDF of per user throughput  $\alpha = 0.5$  and  $\beta = 0.3$ .

Fig. 4 presents a cumulative distribution function (CDF) comparison of per-user throughput across four scheduling algorithms: HCAP, RR, Max CQI, and PF, evaluated under  $\alpha = 0.5$  and  $\beta = 0.3$ . The x-axis indicates user throughput values (0 to 500), while the y-axis reflects the proportion of users achieving those throughput levels. HCAP (blue curve) exhibits a more gradual rise, indicating a broader and more evenly distributed allocation of resources among users. In contrast, RR (orange) and PF (purple) rise steeply, suggesting higher concentration around specific throughput values but less adaptive to channel variability. MaxCQI (yellow) shows uneven fairness due to its bias toward high-CQI users. Overall, the plot confirms HCAP's superior balance of efficiency and fairness, delivering diverse throughput without sacrificing equitable user treatment.

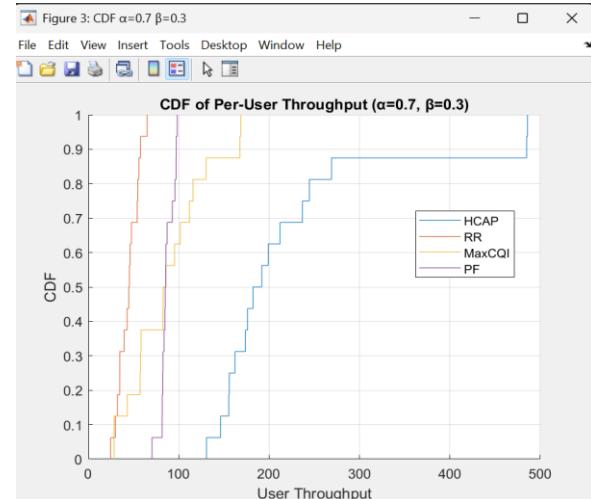


Fig. 5. CDF of per user throughput  $\alpha = 0.7$  and  $\beta = 0.3$ .

Fig. 5 presents the Cumulative Distribution Function (CDF) of per-user throughput under different scheduling algorithms, illustrating how user throughput is distributed in a 5G MU-MIMO system when  $\alpha = 0.7$  and  $\beta = 0.3$ . The HCAP curve (blue) clearly leads, with more users achieving higher throughput compared to other methods, confirming its dominance in prioritizing high-CQI and low-interference users. In contrast, Round Robin (orange) shows a steep rise at lower throughput levels, indicating equal, but inefficient resource allocation. MaxCQI (yellow) has moderate throughput gains with fairness challenges, while Proportional Fair (purple) provides a balanced profile—good fairness but limited throughput. This visualization reinforces HCAP's advantage in striking a performance-fairness trade-off, particularly under aggressive channel-aware prioritization settings.

## VI. DISCUSSION

The results presented in Section V highlight HCAP's effectiveness in balancing throughput and fairness. This section interprets these findings, compares them with prior work, and examines the mechanisms contributing to HCAP's performance.

### A. Trade-off Flexibility via $\alpha$ - $\beta$ Tuning

HCAP's hybrid scoring mechanism allows dynamic adjustment between throughput-oriented and fairness-oriented scheduling. As shown in Fig. 6, increasing  $\alpha$  enhances throughput by prioritizing users with strong channel conditions, while higher  $\beta$  values improve fairness by reducing interference sensitivity. This tunability makes HCAP adaptable to diverse QoS requirements—for instance, prioritizing emergency traffic (high  $\alpha$ ) or ensuring equitable access in crowded networks (high  $\beta$ ).

### B. Role of Clustering in Enhancing Fairness

The use of k-means clustering based on long-term channel statistics played a crucial role in mitigating scheduling bias. By grouping users with similar channel behavior, HCAP ensures that resource competition occurs within clusters rather than across the entire user pool. This localized scheduling prevents users with consistently strong channels from monopolizing resources, thereby improving fairness without significantly compromising throughput.

### C. Comparative Analysis with Existing Schedulers

HCAP's performance gain over traditional schedulers can be attributed to its hybrid and adaptive design:

- Round Robin (RR) provides predictable fairness, but fails to adapt to channel variations, leading to low throughput.
- Max-CQI maximizes throughput by favoring strong channels but severely compromises fairness.
- Proportional Fair (PF) maintains high fairness but underutilizes high-quality channels, limiting throughput.
- HCAP effectively integrates the strengths of these approaches, achieving a superior throughput-fairness

trade-off, as evidenced by both aggregate metrics and CDF curves.

### D. Implications for 5G and Beyond

The robustness of HCAP under varying network conditions supports its suitability for real-time 5G MU-MIMO deployments. Its modular design also allows integration with advanced techniques such as deep reinforcement learning for parameter optimization and network slicing for service-specific scheduling—areas identified for future work.

### E. Limitations and Future Directions

While HCAP shows strong performance in simulation, real-world factors such as imperfect channel estimation, mobility patterns, and multi-cell interference warrant further investigation. Future studies could explore:

- Integration with machine learning for adaptive  $\alpha$ - $\beta$  tuning.
- Validation in hardware testbeds or FPGA-based prototypes.
- Extension to massive MIMO and mm Wave scenarios.

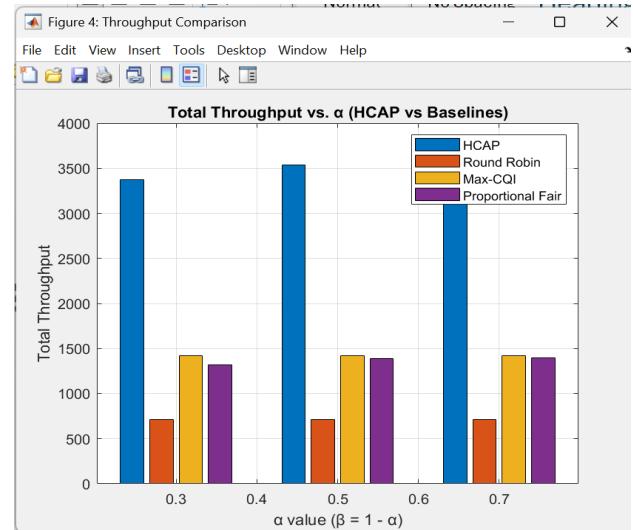


Fig. 6. Total throughput vs  $\alpha$ .

TABLE I. PERFORMANCE COMPARISON OF SCHEDULING ALGORITHMS ( $A = 0.7, B = 0.3$ )

Scheduler	Total Throughput (Units)	Jain's Fairness Index
Round Robin (RR)	1385.21	~0.99
Proportional Fair (PF)	1387.52	~0.98
Max-CQI	2980.45	~0.65
HCAP (Proposed)	3607.56	0.82

## VII. CONCLUSION

The Hybrid Channel-Aware Prioritization (HCAP) scheduler presented in this study demonstrates a robust and scalable solution for resource allocation in Multi-User MIMO systems under 5G communication standards. By integrating normalized CQI and interference metrics into a tunable

prioritization framework, and leveraging clustering techniques to reduce scheduling bias, HCAP achieves a dynamic balance between throughput and fairness. The simulation results validate its superiority over conventional schedulers, with notable improvements in system capacity and equitable resource distribution. These outcomes affirm the scheduler's adaptability to diverse network conditions and its potential for deployment in real-time environments. Future work may explore its extension into machine learning-based scheduling and integration with network slicing for enhanced Quality of Service provisioning in next-generation wireless networks.

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