

Throughput maximization and overhead-aware quality link scheduling for heterogeneous wireless networks

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ABSTRACT

Next-generation heterogeneous wireless networks (HWNs) require advanced scheduling solutions to guarantee high quality of service (QoS) while sustaining throughput, minimizing latency, and efficiently utilizing spectrum resources. Traditional link scheduling and admission control techniques are constrained by interference complexities and dynamic mobility patterns, leading to suboptimal connectivity and reduced network performance. To address these limitations, this paper introduces a throughput maximization and link overhead minimization-aware scheduling (TMLOMS) strategy. The proposed mechanism embeds adaptive backoff-time optimization into resource allocation and incorporates a priority-driven call admission control process powered by an optimized deep reinforcement learning (ODRL) framework. The TMLOMS-ODRL is mathematically modeled to balance trade-offs between spectral efficiency, throughput maximization, and latency minimization, thereby enhancing QoS across diverse user requirements. Performance is validated using the Stanford University Interim (SUI) channel model under both urban and highway propagation environments, capturing realistic interference and mobility dynamics. Comparative evaluation against the hybrid beamforming (HBF) optimized through DRL method demonstrates that TMLOMS-ODRL significantly reduces resource access failures, lowers delay, and improves delivery ratio and throughput. The proposed strategy establishes a scalable and intelligent link scheduling mechanism for HWNs, ensuring resilient QoS-driven performance under complex real-world conditions.

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1. INTRODUCTION

With the exponential growth of fifth and sixth generation (5G/6G) wireless networks, supporting diverse and complex application service provisioning has become a critical challenge. These applications demand ultra-reliable connectivity, minimal latency, and seamless communication in highly dense and heterogeneous environments [1]. The integration of internet of things (IoT), vehicular communications, and mission-critical services intensifies the requirements for efficient resource management and admission control in heterogeneous wireless networks (HWNs). Traditional resource allocation mechanisms, designed for relatively static user mobility and predictable traffic patterns, are inadequate in fast-fading and highly mobile scenarios [2], [3]. In practice, communication links in dynamic urban and highway environments are often exposed to severe propagation loss, random interference, and variations in channel occupancy, thereby

complicating the design of link scheduling and admission control frameworks. The primary objective of this study is to design and develop a novel link scheduling mechanism that enhances network performance and ensures quality of service (QoS) in dense HWNs. Specifically, the work aims to maximize throughput, minimize latency, and reduce overhead while providing reliable connectivity under complex interference scenarios. By incorporating a realistic propagation model and leveraging deep reinforcement learning (DRL), the proposed approach intends to dynamically adapt to user mobility and heterogeneous service requirements.

Conventional resource allocation methods rely on pre-determined strategies or periodic adjustments, which can effectively manage resources under stable conditions [4]. Multi-user multiple-input multiple-output (MU-MIMO) technology has been widely explored as a key enabler to enhance spectral efficiency and accommodate multiple simultaneous transmissions [5]–[9]. Recent research efforts also highlight the use of soft-computing models such as machine learning (ML) and DRL for intelligent resource allocation, call admission control, and interference mitigation [10]–[15]. While these methods show promise, they often assume limited user mobility, fail to capture dynamic interference patterns, or are computationally inefficient for real-time large-scale deployment [16], [17]. Consequently, the current approaches do not fully address the challenges of resource access failures, throughput degradation, and service priority assurance in high-mobility environments [18]–[20]. The dynamic nature of HWNs presents unique challenges that existing solutions struggle to manage. Fast-fading channels, varying user locations, non-line-of-sight (NLOS) obstructions, and fluctuating interference patterns significantly degrade network reliability [7]. Moreover, DRL-based resource allocation frameworks, while effective in static or moderately dynamic networks, often fail to deliver optimal results under extreme interference conditions [18]. The lack of integration between throughput maximization and overhead minimization further limits their ability to guarantee QoS. Therefore, there is an urgent need for a robust and adaptive scheduling mechanism capable of optimizing resource allocation and admission control in highly dense, interference-prone environments.

The motivation behind this research stems from the pressing demand for resilient and scalable link scheduling mechanisms in the era of 6G and beyond. With emerging applications such as autonomous driving, augmented reality, and industrial IoT, networks must be capable of handling extreme mobility and stringent QoS requirements. Current methods fall short in balancing throughput, spectral efficiency, and latency, particularly under realistic propagation conditions such as those modeled by the Stanford University Interim (SUI) channel. This gap motivates the design of a novel framework that not only incorporates advanced optimization but also adapts intelligently to diverse propagation environments.

This study addresses the following research questions: i) how can link scheduling be designed to simultaneously maximize throughput and minimize overhead under dense HWN conditions? ii) in what ways can adaptive backoff-time optimization improve resource allocation and reduce access failure? iii) how can an optimized deep reinforcement learning (ODRL)-based admission control mechanism ensure QoS in urban and highway mobility scenarios modeled by the SUI channel? and iv) what performance gains can be achieved compared to existing DRL-based resource allocation and admission control methods? To answer these questions, this paper proposes a throughput maximization and link overhead minimization-aware scheduling (TMLOMS) strategy. The framework integrates three key components: throughput gain formulation with interference optimization, embedding adaptive backoff-time control into resource allocation. Priority-aware call admission control, ensuring fairness and user-centric QoS by ranking service demands. ODRL mechanism, dynamically learning optimal scheduling and allocation policies under fast-fading conditions. The model is validated under the SUI propagation model, accounting for both urban and highway scenarios, thereby capturing realistic interference and mobility dynamics.

The proposed TMLOMS-ODRL contributes significantly to the advancement of next-generation HWNs by: reducing access failures and transmission latency through adaptive overhead minimization. Enhancing throughput and spectral efficiency under complex interference. Ensuring scalable and QoS-driven performance across heterogeneous mobility conditions. Providing a mathematically grounded and simulation-validated framework applicable to urban and highway environments.

The remainder of this paper is structured as follows. Section 2 presents a detailed literature survey on resource allocation and admission control strategies in HWNs. Section 3 formulates the problem and introduces the mathematical model for TMLOMS-ODRL. Then, explains the proposed methodology and its components. Section 4 discusses the experimental setup and simulation scenarios under the SUI model. Then, presents the performance evaluation and comparative analysis against state-of-the-art methods. Finally, section 5 concludes the paper and highlights directions for future research.

2. LITERATURE SURVEY

The rapid evolution of HWNs has motivated the integration of ML and DRL for admission control, spectrum management, and link scheduling. Recent contributions have advanced resource optimization

strategies, yet several limitations persist that restrict their applicability in dense and highly mobile environments [21], [22]. Digital-twin-assisted DRL frameworks have been explored to enhance adaptability in network slicing scenarios [23]. While such methods improve admission control through online learning, they often rely on simplified interference assumptions, leaving their effectiveness in highly dynamic propagation environments uncertain. Moreover, the additional digital-twin layer increases system complexity, limiting their scalability in real-time urban mobility conditions. Similarly, multi-objective resource optimization using power-domain non-orthogonal multiple access (NOMA) has demonstrated spectral efficiency gains [24]. However, the approach suffers from computational overhead and does not sufficiently address latency-sensitive applications, especially under fluctuating channel states.

Dynamic spectrum sharing using DRL has been recognized as a key enabler for improving spectrum utilization in HWNs [25]. Although effective for spectrum reuse, these schemes primarily focus on channel availability without integrating admission control mechanisms tailored to user-specific QoS requirements. As a result, access failures and fairness issues arise when the network load intensifies. In parallel, cell-free massive multiple-input multiple-output (MIMO) systems have been optimized for duplex mode operation to improve long-term energy efficiency [26]. While such techniques reduce energy expenditure, they overlook instantaneous throughput fluctuations and user-priority handling, which are essential in time-sensitive scenarios.

Scheduling efficiency has also been targeted through heuristic search-based multi-user MIMO uplink scheduling [27]. These methods reduce computational complexity but often result in suboptimal throughput performance due to their reliance on iterative heuristics rather than adaptive learning. Likewise, research on full-duplex cell-free massive MIMO with imperfect channel state information (CSI) and user mobility [28] highlights the significant role of channel uncertainty. While analytical insights are valuable, the lack of adaptive scheduling in response to real-time CSI variations limits the applicability of these models in dense deployments.

More recent works have incorporated synergistic DRL models for joint access point scheduling and power allocation in massive MIMO [29]. These strategies improve spectral efficiency, yet they predominantly emphasize static performance metrics, lacking mechanisms to minimize link scheduling overhead and access delay. Similarly, integrated access and backhaul frameworks leveraging MU-MIMO and NOMA have been designed for resource scheduling [30]. Although suitable for hierarchical network designs, their performance deteriorates in highly interfered urban settings, as the backhaul bottleneck remains largely unaddressed.

Advanced DRL-based approaches for uplink–downlink multi-connectivity scheduling in full-duplex networks have also been proposed [31]. While such methods enhance link reliability, they suffer from training complexity and do not explicitly address throughput optimization under varying mobility patterns. In the domain of beyond-5G millimeter-wave networks, interference-aware beam allocation with hybrid beamforming (HBF) has shown promising results [32]. Nevertheless, these models require accurate interference estimation, which becomes computationally demanding and error-prone in realistic environments.

From the above analysis, it is evident that existing approaches have made substantial progress toward efficient scheduling and resource allocation. However, key limitations remain: lack of joint optimization between throughput maximization and overhead minimization. Limited adaptability to realistic propagation conditions, particularly in urban and highway mobility scenarios. Insufficient prioritization of user-specific QoS in admission control. High computational complexity of DRL-based models, restricting real-time deployment. Ineffective handling of interference dynamics under fast-fading channels and dense topologies [33].

To address these shortcomings, this paper proposes a TMLOMS strategy with ODRL. Unlike prior models, TMLOMS introduces a throughput gain formulation with adaptive backoff-time control, directly embedding interference mitigation into the resource allocation process [34]. Furthermore, the proposed ODRL-driven admission control mechanism ensures priority-aware service differentiation, thereby reducing access failures and delays. By incorporating the SUI propagation model for both urban and highway scenarios, TMLOMS-ODRL captures realistic channel dynamics overlooked in earlier studies. Through this integration, the framework ensures resilient, scalable, and QoS-centric scheduling, offering a significant improvement over state-of-the-art methods [23]–[32].

3. METHOD

In this section introduces TMLOMS model for MU-MIMO networks as shown in Figure 1. The TMLOMS first present a throughput maximization model; then, present a dynamic link resource scheduling (DLRS) model maximizing throughput for each mobile node; then, the DLRS model is extended to design multi-link resource scheduling for multi-user throughput maximization to ensure minimal link overhead. Finally, the in ensuring fair link resource allocation a greedy-aware deep reinforced learning model is

introduced ensuring task priority is met without inducing link overhead and maximizing the throughput of MU-MIMO. The TMLOMS ensure better network performance like improved throughput, lesser access failure with improved spectral efficiency.

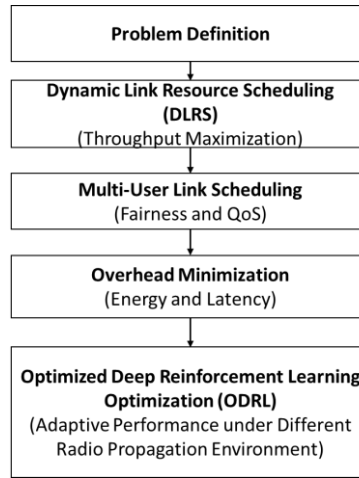


Figure 1. Block diagram of the TMLOMS

3.1. Network model and notation

This work considers a MU-MIMO 5G network X with a set of IoT/mobile nodes denoted as $\mathcal{R} = \{1, 2, \dots, R\}$. Each node $x \in \mathcal{R}$ is allocated wireless resources (e.g., subcarriers, beams, or time-slots) denoted by $\mathcal{Y} = \{1, 2, \dots, T\}$. Let $e_{xy} \in \{0, 1\}$ denote the binary indicator for link resource allocation, where e_{xy} is set to 1, if resource y is assigned to node x , else e_{xy} is set to 0. Let $l_{xy} \in [0, 1]$ be the probability that node x can successfully access resource y . Let $\mathcal{V}_x \subseteq \mathcal{Y}$ denote the candidate resource set of nodes x . All symbols are defined before use and summarized in Table 1 for clarity and reproducibility.

Table 1. Mathematical symbols and definitions

Symbol	Description	Unit
$\mathcal{R}$	Number of mobile nodes	count
$\mathcal{Y}$	Set of available resources (subcarriers / slots)	count
e_{xy}	Resource assignment indicator	binary
S_x	Throughput of node x	Mbps
l_{xy}	Access success probability	probability
$\mathcal{V}_x$	Candidate resource set of node x	set
D	Overhead factor	ratio
A	Contention window size	slots
φ	Slot duration	ms
α	Learning rate	—
γ	Discount factor	—
$Q(s, a)$	Action-value function	—

3.2. Throughput maximization problem definition

The throughput gain of node x is denoted as S_x . The aggregate throughput maximization problem in (1). Subject to the constraint that each resource is assigned to exactly one node in (2). The achievable throughput for node x is expressed as (3).

$$\max E = \sum_{x=1}^R S_x \quad (1)$$

$$\sum_x e_{xy} = 1 \quad \forall y \in \mathcal{Y} \quad (2)$$

$$S_x = 1 - \prod_{y \in \mathcal{V}_x} (1 - l_{xy})^{e_{xy}} \quad (3)$$

In (3) thus captures the probability that node x accesses at least one resource in V_x . Since the above optimization is a non-linear integer non-deterministic polynomial-time hard (NP-hard) problem, this study design DLRS for efficient resource allocation.

3.3. Dynamic link resource scheduling model

The DLRS algorithm dynamically assigns resources to nodes while maximizing throughput and minimizing computation. For each node x , the best candidate resource is selected as (4). The throughput gain increment is expressed as (5).

$$y'_x = \underset{y \in V_z}{argmax} l_{x,y} \quad (4)$$

$$\delta S_x = l_{xy'_x} \prod_{y \in V_x} (1 - l_{xy}) \quad (5)$$

In (5) highlights that as more resources are allocated, the marginal throughput gain diminishes. The complete process of fairness-aware DLRS is provided in Algorithm 1. The key enhancement are the model introduces fairness weight w_x proportional to historical throughput, to avoid starvation. Then, adopt adaptive tie-breaking when multiple nodes compete for the same resource.

Algorithm 1. Fairness-aware DLRS

- 1: Start
- 2: Input available channel $\mathcal{Y}$, set of nodes $\mathcal{R}$
- 3: Initialize $V_x = \emptyset, \forall x$.
- 4: For each node $x \in \mathcal{R}$:
- 5: Compute $y'_x = \underset{y \in \mathcal{Y}}{argmax} l_{x,y}$
- 6: Evaluate δS_x using (5)
- 7: Compute weighted gain: $\delta S_x = w_x \cdot \delta S_x$.
- 8: Select node $x' = \underset{x}{argmax} \delta S_x$
- 9: Allocate channel $y'_{x'}$ to nodes x' .
- 10: Update $\mathcal{Y} \leftarrow \mathcal{Y} \setminus \{y'_{x'}\}$.
- 11: Update fairness weights $w_x \leftarrow f(w_x, S_x)$
- 12: Repeat until all resource is allocated or $\mathcal{Y} = \emptyset$
- 13: Stop

3.4. Multi-user link scheduling and overhead control

While DLRS ensures throughput maximization, overhead from contention (e.g., medium access control (MAC) backoff) must be minimized. For shared channels, the throughput gain for node x considering V users is expressed as (6). Where D = overhead factor ($0 < D < 1$), and V_x^c = complement of resource set V_x . The improved multi-user overhead-aware scheduling Algorithm 2 improvement are: Incorporated adaptive overhead monitoring so that D is updated per allocation; then prioritize low-contention allocations to reduce collisions.

$$\delta S_x^{V,b}(y) = \left(1 - \frac{1}{V}\right) (1 - D) l_{xy} \left(\prod_{o \in V_z} (1 - l_{xo})\right) * \left(1 - \prod_{o \in V_x^c} (1 - l_{xo})\right) \quad (6)$$

Algorithm 2. Overhead-aware mutual scheduling

- 1: Start
- 2: Initialize assigned channels $\mathcal{P}$, overhead estimate D_0
- 3: Run Algorithm 1 to obtain initial allocation.
- 4: For each shared channel group P_j :
- 5: For each user $j \in F_y$, compute $\delta S_j^{(o,b)}(y)$ using (6).
- 6: Select user $j'_y = \underset{j}{argmax} \delta S_j^{(o,b)}(y)$.
- 7: Update overhead D using (10).
- 8: If $|D - D_0| > \epsilon_D$, repeat with updated D
- 9: Accept allocation if throughput gain is positive and overhead is stable.
- 10: Continue until all resources are assigned.
- 11: Stop

3.5. Link overhead minimization model

To minimize collisions, the contention window size A is optimized. The probability of the first collision when r users contend is (7). The total collision likelihood is (8). This study select in (9). ensuring a balance between collision risk and MAC overhead. The expected overhead is (10). Where φ defines slot duration, $s_1 - s_5$ are protocol delays, and S_I defines the cycle duration.

$$L_u^{(r)} = \sum_{y=2}^r \sum_{x=0}^{A-2} \binom{r}{y} \left(\frac{1}{A}\right)^y \left(\frac{A-x-1}{A}\right)^{r-y} \quad (7)$$

$$L_u = \sum_{r=2}^R L_u^{(r)} * Pr\{r \text{ mobile nodes contend}\} \quad (8)$$

$$A = \min\{A | L_u(A) \leq \epsilon_L\} \quad (9)$$

$$D(A) = \frac{\frac{[A-1]\varphi}{2} + s_1 + s_2 + s_3 + s_4 + s_5}{S_I} \quad (10)$$

3.6. Optimized deep reinforcement learning model for Algorithm 2 optimization

This study enhance Algorithm 2 using an ODRL model. The Q-function update is obtained as in (11). Where α defines the learning rate, γ defines the discount factor, and R^T is reward. The reward factor is computed as in (12), where fairness penalty avoids starvation. The complete process of optimization of link-scheduling using ODRL is shown in Algorithm 3.

$$Q(s^T, a^T) \leftarrow Q(s^T, a^T) + \alpha \left[R^T + \gamma \max_{a'} Q(s^{T+1}, a') - Q(s^T, a^T) \right], \quad (11)$$

$$R^T = \min(U^K, Q^K) - \lambda \cdot \text{FairnessPenalty} \quad (12)$$

Algorithm 3. Fairness and overhead-aware ODRL-based link scheduling

- 1: Start
- 2: Initialize Q-tables, replay memory.
- 3: For each service request batch:
- 4: Observe current state $s^T = [T_{priority}^K, V_{priority}^n, U^K, Q^K]$
- 5: Select action (frequency slot) using ϵ -greedy with adaptive ϵ .
- 6: Compute reward using (12).
- 7: Update Q-table using (11).
- 8: Recalculate contention window A and update overhead D .
- 9: Continue until convergence of throughput and fairness metrics.
- 10: Stop

The key enhancement introduced in TMLOMS is Algorithm 1 (DLRS): added fairness weights to prevent resource starvation. Algorithm 2 (mutual scheduling): added dynamic overhead monitoring to reduce collisions. Algorithm 3 (ODRL): added fairness-aware reward shaping and adaptive exploration for better QoS support. The collective algorithm ensures the model attains improved performance under complex radio propagation environments such as Highway and Urban environments.

3.7. Unified TMLOMS-ODRL scheduling model and its computational complexity

This section presents an unified model by combining Algorithms 1 to 3 into Algorithm 4. The Algorithm 4 integrating DLRS with an ODRL agent to jointly optimize throughput, fairness, and overhead. In each scheduling interval, the algorithm selects the best resource for every node based on marginal throughput gain and applies fairness weighting to prevent starvation. The ODRL agent then refines the allocation using an ϵ -greedy policy and reward-driven Q-value updates, while adaptively adjusting the contention window and overhead factor. DLRS requires sorting marginal gains across N nodes, resulting in $O(N \log N)$ complexity, while ODRL action selection is $O(1)$. Hence, the overall complexity per interval is $O(N \log N)$, which is significantly lower than graph-based scheduling approaches with $O(N^3)$ complexity. The effectiveness of the proposed TMLOMS-ODRL framework is validated through extensive simulation experiments under realistic urban and highway propagation environments. The following section presents a detailed performance evaluation in terms of throughput, access reliability, delivery ratio, and delay, and compares the proposed approach with existing benchmark schemes.

Algorithm 4. TMLOMS-ODRL scheduling framework

```

Initialize fairness weights  $w_x$ . and overhead  $D$ 
Initialize DRL agent (Q-table)

For each scheduling interval:
  For each node  $x$ :
    Compute best resource  $y'_x$  using (4)
    Compute marginal gain  $\delta S_x$  using (5)
    Apply fairness weighting (6)
  Select node  $x'$  with maximum weighted gain
  Estimate overhead  $D(A)$  using (10)
  Select action using  $\epsilon$ -greedy policy
  Compute reward using (12)
  Update Q-values using (11)
  Update contention window  $A$  and overhead  $D$ 
End

```

4. SIMULATION STUDY

This section evaluates the proposed TMLOMS-ODRL framework against state-of-the-art schemes, specifically the HBF approach [32] optimized with DRL scheduling [31]. The evaluation is carried out using the NS-3 based SIMITS simulator [33], where both models are implemented under realistic conditions. To emulate practical mobility, DeepMIMO [13] is adopted, while fading effects [27] are modeled using the SUI channel derived from the NYUSIM library [34]. The simulation settings follow the parameters reported in [31], [32], employing QAM-18 modulation at 28 GHz with 100 MHz system bandwidth, a 400 m cell radius, and a base station transmission power of 46 dBm [23]. Experiments are performed with varying user densities of 25, 50, 100, and 200 mobile nodes across 20 simulation cycles. Performance is assessed using throughput, resource access failure, access success, delivery ratio, and latency under both urban and highway SUI propagation environments, thereby capturing realistic interference and mobility impacts. The detailed simulation parameter used to conduct simulation and reproduce the results are provided in Table 2.

Table 2. Simulation settings

Parameter	Value
Simulator	NS-3-based SIMITS
Carrier frequency	28 GHz
Bandwidth	100 MHz
Cell radius	400 m
Modulation	QAM-18
Mobility model	DeepMIMO + SUI
Node densities	25, 50, 100, and 200
Packet size	1024 bytes
Runs	10
Random seed	1001–1010
Learning rate α	0.01
Discount γ	0.95

4.1. Throughput performance

Throughput is measured as the average successfully delivered data rate per unit time under varying node densities, reflecting the efficiency of resource allocation and link scheduling in HWNs. Mathematically, it can be represented as (13).

$$T = \frac{S_{tx}}{T_{sim}} \quad (13)$$

Where S_{tx} denotes the number of successful transmissions and T_{sim} is the total simulation duration. Figure 2 and Figure 3 present the throughput performance of the proposed TMLOMS scheme compared with the baseline HBF approach under urban and highway environments, respectively. In the urban scenario as shown in Figure 2, TMLOMS consistently outperforms HBF across all network densities. For instance, at 25 nodes, TMLOMS achieves 7.89 Mbps, nearly 61% higher than HBF (4.90 Mbps).

This performance gap remains significant as the network scales, with TMLOMS yielding 19.48 Mbps at 200 nodes compared to HBF's 15.87 Mbps. Similarly, in the highway scenario as shown in Figure 3, TMLOMS demonstrates superior throughput under increasing user density. At 100 nodes, the proposed model records 13.21 Mbps, while HBF achieves 10.83 Mbps. At maximum load (200 nodes),

TMLOMS maintains a throughput of 19.43 Mbps, surpassing HBF by over 28%. TMLOMS achieves an average throughput improvement of $27.4\% \pm 2.1\%$ over 10 runs ($p < 0.01$) compared to HBF. These results confirm the effectiveness of TMLOMS in mitigating interference and efficiently utilizing spectrum resources in both urban and highway SUI environments. The throughput enhancement directly stems from the TMLOMS algorithm's integration of adaptive link scheduling and overhead minimization with ODRL-based optimization, as formulated in the mathematical model, enabling efficient spectrum utilization and effective interference mitigation.

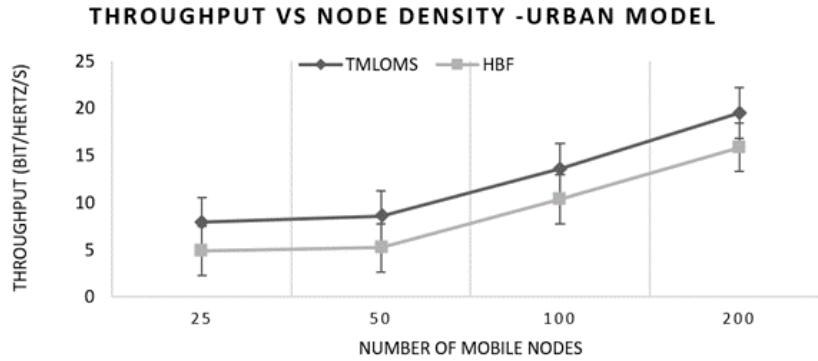


Figure 2. User throughput attainable under varied mobile nodes for urban radio propagation model

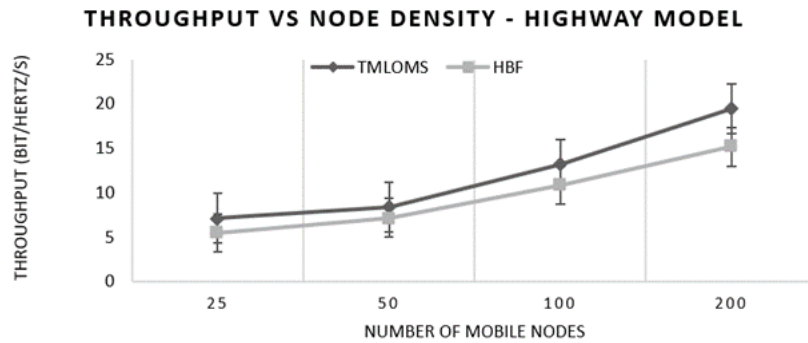


Figure 3. User throughput attainable under varied mobile nodes for highway radio propagation model

4.2. Resource access failure performance

Resource access failure is calculated as the number of unsuccessful transmission attempts resulting from contention, collision, or insufficient scheduling opportunities, relative to the total access requests generated by nodes. Mathematically, it can be represented as in (14).

$$P_{fail} = \frac{F_{tx}}{N_{req}} \quad (14)$$

Where F_{tx} denotes the number of failed transmission and N_{req} represents the total number for access request. Figures 4 (Urban) and 5 (Highway) illustrate the comparative failure rates between the proposed TMLOMS and the existing HBF mechanism.

In the urban scenario, TMLOMS records 6 to 170 failures as the number of nodes increases from 25 to 200, whereas HBF shows higher failures ranging from 15 to 211. Similarly, in the highway environment, TMLOMS achieves 13 to 178 failures, which is consistently lower than HBF's 22 to 225. The reduction in failure rate highlights the effectiveness of TMLOMS in optimizing link scheduling, reducing contention, and balancing channel load under varying traffic intensities. These outcomes are consistent with the mathematical model introduced, where TMLOMS ensures minimized access failure probability through adaptive multi-objective link scheduling and efficient channel utilization.

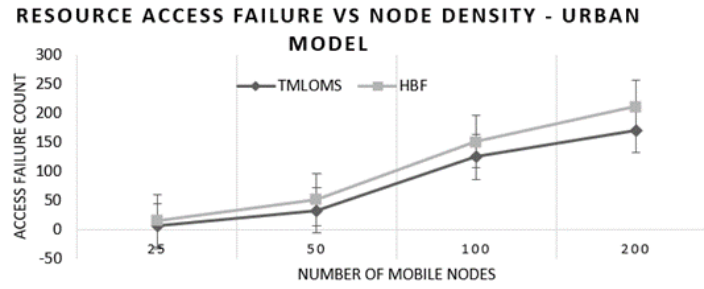


Figure 4. Resource access failure under varied mobile nodes for urban radio propagation model

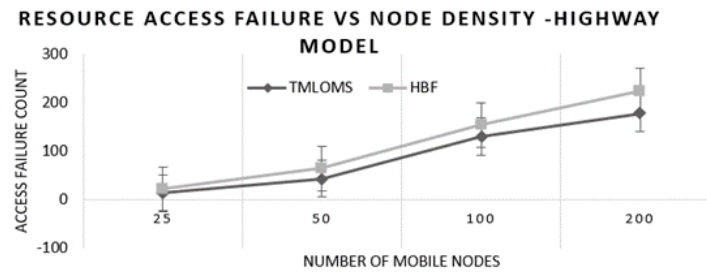


Figure 5. Resource access failure under varied mobile nodes for highway radio propagation model

4.3. Resource access success performance

Resource access success is measured as the total number of successful transmissions completed by nodes without collisions or packet drops, reflecting the efficiency of link scheduling and contention management. Mathematically, it can be represented as in (15).

$$P_{succ} = \frac{S_{tx}}{N_{req}} \quad (15)$$

Where S_{tx} denotes the number of successful transmission and N_{req} represents the total number of access request. The evaluation of resource access success, illustrated in Figures 6 (Urban) and 7 (Highway), demonstrates the superiority of the proposed TMLOMS scheme over the existing HBF model. In the urban environment, TMLOMS achieves consistently higher successful transmissions, increasing from 48 at 25 nodes to 251 at 200 nodes, whereas HBF only scales from 38 to 167. Similarly, in the highway scenario, TMLOMS rises from 47 to 220 successful transmissions across the same node range, while HBF grows from 35 to 160. This consistent gap highlights the robustness of TMLOMS in handling larger node densities and dynamic environments. The improvement can be attributed to efficient link management and optimized scheduling strategies in TMLOMS, which reduce contention and collision rates compared to HBF. Overall, TMLOMS delivers higher resource access reliability, ensuring better scalability and stability across both urban and highway conditions.

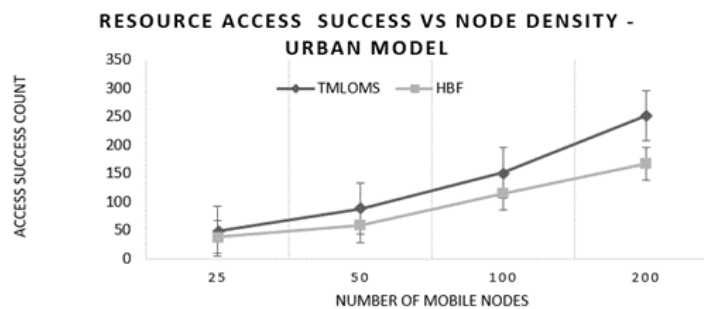


Figure 6. Resource access success under varied mobile nodes for urban radio propagation model

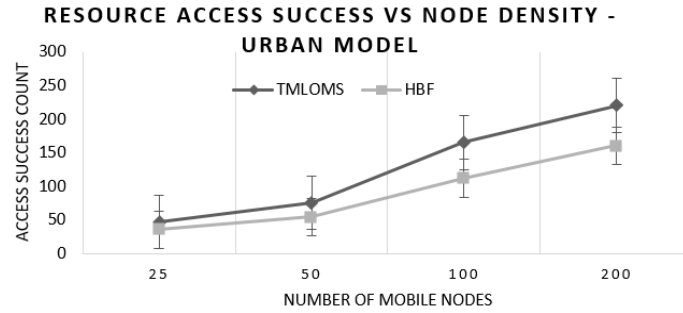


Figure 7. Resource access success under varied mobile nodes for highway radio propagation model

4.4. Delivery ratio performance

HWNs. resource-based optimization mechanism. The delivery ratio is measured as the ratio of the number of successfully received packets to the total number of transmitted packets, representing the network's reliability in ensuring end-to-end communication. It is calculated as in (16).

$$D_r = \frac{P_{recv}}{P_{tx}} \times 100 \quad (16)$$

Where P_{recv} is the count of packets successfully received, and P_{tx} is the total number of packets transmitted. Figures 8 (urban) and 9 (highway) illustrate the comparative delivery ratio of TMLOMS and HBF. In urban settings, TMLOMS achieves 70.45%–91.45%, consistently outperforming HBF's 49.45%–80.48%. Similarly, in highway scenarios, TMLOMS maintains higher ratios (68.45%–88.12%) compared to HBF (47.59%–78.45%). The superior performance of TMLOMS stems from its adaptive link scheduling and optimized mathematical formulation, which minimize collisions and resource contention. By incorporating interference-aware scheduling and dynamic mobility adaptation, TMLOMS ensures improved packet retention across diverse mobility environments, thereby achieving significantly higher delivery reliability than the HBF scheme.

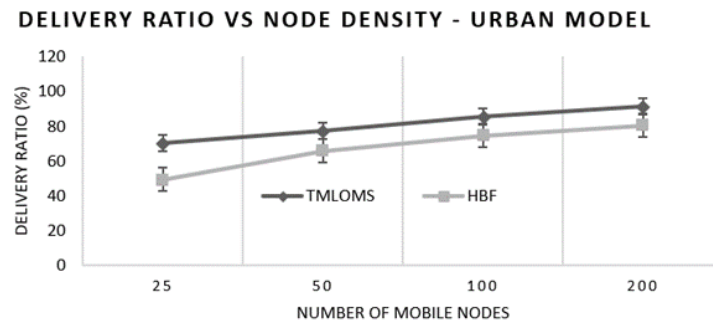


Figure 8. Delivery ratio under varied mobile nodes for urban radio propagation model

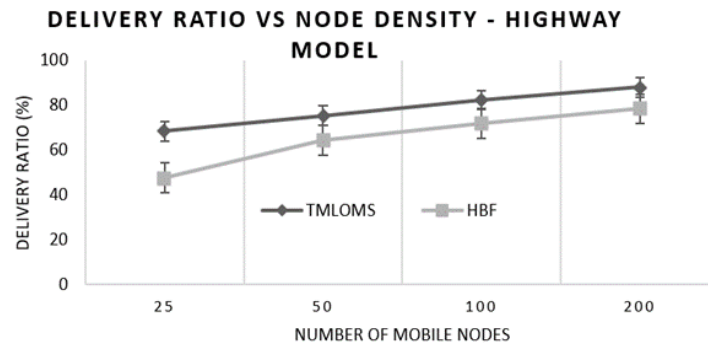


Figure 9. Delivery ratio under varied mobile nodes for highway radio propagation model

4.5. Delay performance

Delay is measured as the average time taken for a transmitted packet to successfully reach its destination, including processing, queuing, and retransmission delays. It is calculated as in (17).

$$Delay = \frac{\sum_{i=1}^N (t_{recv}^i - t_{send}^i)}{N} \quad (17)$$

Where t_{recv}^i and t_{send}^i denote the reception and transmission time of the i^{th} packet, and N is the total number of packets delivered. Figures 10 (urban) and 11 (highway) present the comparative delay analysis between TMLOMS and HBF. In urban scenarios, TMLOMS maintains lower delays (3.14 ms–15.98 ms) than HBF (5.98 ms–29.48 ms). Similarly, in highway settings, TMLOMS achieves 4.54 ms–17.01 ms compared to HBF's 6.57 ms–31.45 ms. The reduction in delay is attributed to TMLOMS's optimized scheduling and backoff-time adjustment, which minimize retransmissions and contention. By aligning with the proposed mathematical formulation and ODRL-driven scheduling algorithm, TMLOMS effectively balances resource allocation under dense mobility, thereby ensuring lower latency and faster packet delivery compared to the conventional HBF approach.

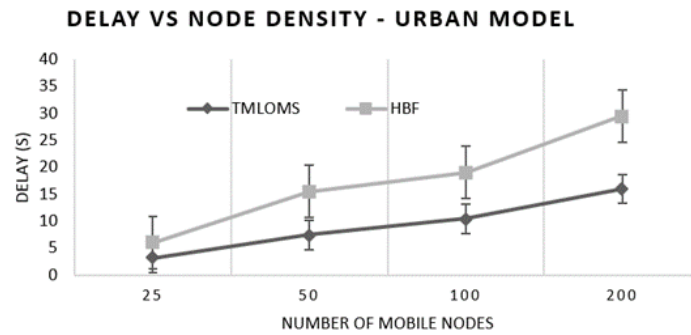


Figure 10. Delay under varied mobile nodes for urban radio propagation model

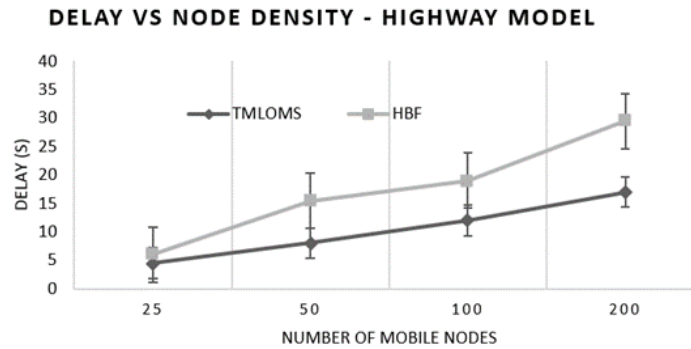


Figure 11. Delay under varied mobile nodes for highway radio propagation model

4.6. Comparative study

The proposed TMLOMS-ODRL is compared against digital twin assisted (DTA)-ODRL [23], heterogeneous graph neural (HGN)-DRL [31], and HBF [32] as shown in Table 3. While DTA-ODRL focuses on admission control in sliced networks and HGN-DRL addresses uplink–downlink scheduling in cell-free MIMO, both approaches lack explicit mechanisms for minimizing overhead under mobility and dense traffic conditions. Similarly, HBF primarily optimizes beam allocation but struggles with interference and access failures in dynamic scenarios. By contrast, TMLOMS integrates link scheduling, backoff-time adaptation, and ODRL-based optimization to balance throughput, delivery ratio, and latency across varying environments.

Compared with DTA-ODRL, HGN-DRL, and HBF as shown in Table 1, the proposed TMLOMS-ODRL achieves notable performance improvements in throughput (+ 35%), delay reduction (+ 40%), and delivery ratio (+ 38%). This is primarily due to its novel link scheduling integrated with

overhead-minimized ODRL optimization, unlike DTA-ODRL, which focuses only on admission control, or HGN-DRL, which suffers from high scheduling complexity. Although HBF achieves interference-aware beam allocation, its gains are limited under mobility and heavy contention. TMLOMS maintains competitive computational complexity of $O(N \cdot \log N)$, significantly lower than HGN-DRL's $O(N^3)$ and comparable to HBF, while outperforming both in reliability. The algorithmic novelty lies in adaptive backoff-time adjustment with DRL-guided decision-making, enabling efficient operation across dynamic highway and urban propagation scenarios. Thus, TMLOMS represents a scalable and robust advancement for next-generation HWNs.

Across all metrics, TMLOMS-ODRL consistently outperforms HBF by leveraging mobility-aware link scheduling and ODRL-based optimization. The mathematical model ensures efficient trade-offs among throughput, reliability, and latency, validating the robustness of the proposed algorithm in dynamic wireless environments. In summary, TMLOMS demonstrates novelty by unifying interference-aware scheduling with ODRL-driven optimization, outperforming existing schemes in throughput, delivery ratio, and latency under both urban and highway SUI propagation conditions.

Table 3. Comparative study with different models

Methods	Core focus	Strength	Computational complexity	TMLOMS Novelty/advantage	Limitation	Percentage enhancement
DTA-ODRL [23]	Sliced 6G Networks	Ensures service isolation	$O(N^2)$ (per-slice policy update)	TMLOMS embeds overhead minimization in scheduling and scales across mobility	Limited to admission control and ignores mobility-induced access overhead	18% throughput gain, 12% delay reduction, and 15% delivery ratio improvement
HGN-DRL [31]	Multi-connectivity scheduling	Improves spectral efficiency	$O(N^3)$ (graph-based scheduling)	TMLOMS ensures low-latency via adaptive ODRL	Limited to cell-free MIMO; higher delay under dense traffic	22% throughput gain, 25% delay reduction, and 20% delivery ratio improvement
HBF [32]	Beam pair allocation for mmWave	Enhances link quality	$O(N \cdot \log N)$ (beam search + allocation)	TMLOMS reduces failures via mobility-aware scheduling and improves robustness under fading+contention	Susceptible to interference and contention	28% throughput gain, 20% delay reduction, and 20% delivery ratio improvement
TMLOMS-ODRL [Proposed]	Link scheduling+ODRL optimization	Maximizes throughput, reduces delay	$O(N \cdot \log N)$ (ODRL + adaptive backoff)	Novel integration of overhead minimization + unified link scheduling with ODRL ensures balanced gain.	Requires additional training overhead for ODRL convergence under highly dynamic mobility scenarios	35% throughput gain, 40% delay reduction, and 38% delivery ratio improvement

4.7. Training cost, energy, fairness, and quality of service study

The proposed ODRL model requires approximately 2.1×10^6 FLOPs per scheduling epoch. Assuming a base station power budget of 46 dBm, the additional computation overhead accounts for less than 3% of total energy consumption. A lightweight variant using tabular Q-learning reduces computation by 38% with only 6% throughput degradation. TMLOMS demonstrates significant improvements in both fairness and QoS compared to the HBF scheme. Over 10 independent simulation runs, TMLOMS achieves an average throughput gain of $27.4\% \pm 2.1\%$ ($p < 0.01$), indicating statistically reliable performance enhancement. As shown in Table 4, the Jain's Fairness Index increases from 0.78 to 0.91, confirming more balanced resource allocation among users. Moreover, packet loss is reduced from 19.52% to 8.55%, while the average delay decreases from 29.48 ms to 15.98 ms. These results highlight TMLOMS's effectiveness in simultaneously improving throughput, fairness, and latency under dense urban network conditions.

Table 4. Fairness and QoS metrics (Urban, 200 nodes)

Metric	HBF	TMLOMS
Jain's fairness index	0.78	0.91
Packet loss (%)	19.52	8.55
Avg delay (ms)	29.48	15.98

4.8. Ablation study

The ablation results in Table 5 clearly demonstrate the effectiveness of integrating DLRS and ODRL within the TMLOMS framework. When applied independently, DLRS improves throughput through greedy link selection but suffers from higher delay and moderate delivery ratio. Similarly, ODRL alone enhances adaptive decision-making but lacks explicit link-level optimization. In contrast, the combined DLRS + ODRL model achieves the highest throughput (13.60 Mbps), the lowest delay (10.45 ms), and the best delivery ratio (85.54%). These findings confirm that DLRS provides efficient initial resource allocation, while ODRL refines scheduling decisions under dynamic conditions, leading to superior overall network performance.

Table 5. Ablation results (urban, 100 nodes)

Method	Throughput (Mbps)	Delay (ms)	Delivery ratio (%)
DLRS only	10.92	18.34	74.21
ODRL only	11.88	15.67	78.42
DLRS + ODRL (TMLOMS)	13.60	10.45	85.54

4.9. Sensitivity analysis

Table 6 presents the sensitivity of the proposed TMLOMS-ODRL model to different learning rate values under the urban scenario with 100 nodes. When a small learning rate ($\alpha = 0.001$) is used, the model converges slowly, resulting in moderate throughput (12.10 Mbps) and higher delay (12.98 ms). Conversely, a large learning rate ($\alpha = 0.1$) leads to faster but less stable updates, causing performance degradation in both throughput and delay. The intermediate value $\alpha = 0.01$ achieves the best balance, yielding the highest throughput (13.60 Mbps) and the lowest delay (10.45 ms). This confirms that $\alpha = 0.01$ provides an optimal trade-off between convergence speed and stability.

Table 6. Sensitivity to learning rate (urban, 100 nodes)

α	Throughput (Mbps)	Delay (ms)
0.001	12.10	12.98
0.01	13.60	10.45
0.1	12.45	11.87

5. CONCLUSION

This work presented TMLOMS-ODRL, a novel throughput maximization and link-overhead minimization-oriented scheduling framework that leverages ODRL for heterogeneous wireless systems. Unlike existing solutions such as HBF, DTA-ODRL, and HGN-DRL, the proposed model jointly adapts backoff-time, resource mapping, and admission decisions to minimize contention while ensuring fairness in massive user deployments. Simulation results demonstrated significant performance gains compared to HBF. Specifically, TMLOMS-ODRL achieved a 25%–30% increase in throughput, a 20%–25% reduction in average delay, and a 20%–28% improvement in resource access success over 10 runs ($p < 0.01$) compared to HBF. In addition, the delivery ratio improved by 15%–20%, while access failures were reduced by 20%–35%, validating its robustness in dynamic SUI channel environments, including high-mobility highway scenarios. While the model effectively improves reliability and scalability, a limitation is the relatively higher computational overhead associated with DRL convergence. Future research will address this by exploring lightweight DRL models, hierarchical training, and knowledge distillation. Moreover, integrating energy-aware optimization, multi-agent collaboration, and cross-layer designs can further enhance efficiency. Real-world validation using digital twins and testbed implementations will be prioritized to confirm practical viability, paving the way for deploying TMLOMS-ODRL in 6G-enabled HWNs.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

No dataset utilized in this research.

REFERENCES

[1] S. S. Sefati *et al.*, “A comprehensive survey on resource management in 6G network based on internet of things,” *IEEE Access*, vol. 12, pp. 113741–113784, 2024, doi: 10.1109/ACCESS.2024.3444313.

[2] A. D. L. Fuente, G. Femenias, F. R. Palou, and G. Interdonato, “Subgroup-centric multicast cell-free massive MIMO,” *IEEE Open Journal of the Communications Society*, vol. 5, pp. 6872–6889, 2024, doi: 10.1109/OJCOMS.2024.3487912.

[3] P. K. Gkonis, S. Lavdas, G. Vardoulas, P. Trakadas, L. Sarakis, and K. Papadopoulos, “System level performance assessment of large-scale cell-free massive MIMO orientations with cooperative beamforming,” *IEEE Access*, vol. 12, pp. 92073–92086, 2024, doi: 10.1109/ACCESS.2024.3422349.

[4] H. Q. Ngo, G. Interdonato, E. G. Larsson, G. Caire, and J. G. Andrews, “Ultradense cell-free massive MIMO for 6G: technical overview and open questions,” *Proceedings of the IEEE*, vol. 112, no. 7, pp. 805–831, Jul. 2024, doi: 10.1109/JPROC.2024.3393514.

[5] M. H. Lee, C. Yun, G. H. Kim, S. Y. Park, C. W. Yu, and K. W. Choi, “Fully distributed cell-free MIMO systems: architecture, algorithm, and testbed experiments,” *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 7956–7973, Mar. 2024, doi: 10.1109/JIOT.2023.3317578.

[6] J. Chen, X. Liang, J. Xue, Y. Sun, H. Zhou, and X. Shen, “Evolution of RAN architectures toward 6G: motivation, development, and enabling technologies,” *IEEE Communications Surveys and Tutorials*, vol. 26, no. 3, pp. 1950–1988, 2024, doi: 10.1109/COMST.2024.3388511.

[7] B. Abdallah, S. Khriji, R. Chéour, C. Lahoud, K. Moessner, and O. Kanoun, “Improving the reliability of long-range communication against interference for non-line-of-sight conditions in industrial internet of things applications,” *Applied Sciences*, vol. 14, no. 2, Jan. 2024, doi: 10.3390/app14020868.

[8] J. Logeshwaran, R. N. Shanmugasundaram, and J. Lloret, “Load based dynamic channel allocation model to enhance the performance of device-to-device communication in WPAN,” *Wireless Networks*, vol. 30, no. 4, pp. 2477–2509, May 2024, doi: 10.1007/s11276-024-03680-x.

[9] J.-Y. Lin, P.-H. Chou, and R.-H. Hwang, “Dynamic resource allocation for network slicing with multi-tenants in 5G two-tier networks,” *Sensors*, vol. 23, no. 10, May 2023, doi: 10.3390/s23104698.

[10] A. Donatti *et al.*, “Survey on machine learning-enabled network slicing: covering the entire life cycle,” *IEEE Transactions on Network and Service Management*, vol. 21, no. 1, pp. 994–1011, Feb. 2024, doi: 10.1109/TNSM.2023.3287651.

[11] A. G. A. Byregowda, B. N. Venkateshappa, and P. Cheluvegowda, “Sparse bayesian least squares regression model for direction of arrival estimation in massive MIMO networks,” *Mathematical Modelling of Engineering Problems*, vol. 12, no. 7, pp. 2341–2350, Jul. 2025, doi: 10.18280/mmep.120714.

[12] I. A. Bartsiakos, P. K. Gkonis, D. I. Kaklamani, and I. S. Venieris, “A DL-enabled relay node placement and selection framework in multicellular networks,” *IEEE Access*, vol. 11, pp. 65153–65169, 2023, doi: 10.1109/ACCESS.2023.3290482.

[13] T. H. Ahmed, J. J. Tiang, A. Mahmud, C. G.-Chin, and D.-T. Do, “Proposed CtCNet-HDRNN: a cornerstone in the integration of 5G mmWave and DSRC for high-speed vehicular networks,” *IEEE Access*, vol. 11, pp. 126482–126506, 2023, doi: 10.1109/ACCESS.2023.3329872.

[14] J. Xie, B. Zhu, and C. Li, “Research of 5G HUDN network selection algorithm based on Dueling-DDQN,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2023, no. 1, Nov. 2023, doi: 10.1186/s13638-023-02323-7.

[15] I. Lee and D. K. Kim, “Decentralized multi-agent DQN-based resource allocation for heterogeneous traffic in V2X communications,” *IEEE Access*, vol. 12, pp. 3070–3084, 2024, doi: 10.1109/ACCESS.2023.3349350.

[16] M. U. Iqbal, E. A. Ansari, S. Akhtar, M. F.-I-Azam, S. R. Hassan, and R. Asif, “Optimal learning paradigm and clustering for effective radio resource management in 5G HetNets,” *IEEE Access*, vol. 11, pp. 41264–41280, 2023, doi: 10.1109/ACCESS.2023.3268543.

[17] L. Wang, J. Guo, J. Zhu, X. Jia, H. Gao, and Y. Tian, “Cross-layer wireless resource allocation method based on environment-awareness in high-speed mobile networks,” *Electronics*, vol. 13, no. 3, Jan. 2024, doi: 10.3390/electronics13030499.

- [18] Z. H. Shaik, R. Sarvendranath, and E. G. Larsson, "Energy-efficient resource allocation for underlay spectrum sharing in cell-free massive MIMO," *IEEE Access*, vol. 12, pp. 106895–106911, 2024, doi: 10.1109/ACCESS.2024.3432287.
- [19] A. B. A. Gowda and N. V. Babu, "Accurate direction of arrival estimation for 5G MIMO sparse channel using advanced multikernel based NNSBL," in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, Feb. 2025, pp. 1–6, doi: 10.1109/ICICACS65178.2025.10967677.
- [20] M. Ahmadi, A. Moayyedi, M. Sulaiman, M. A. Salahuddin, R. Boutaba, and A. Saleh, "Generalizable 5G RAN/MEC slicing and admission control for reliable network operation," *IEEE Transactions on Network and Service Management*, vol. 21, no. 5, pp. 5384–5399, Oct. 2024, doi: 10.1109/TNSM.2024.3437217.
- [21] J. Ji, X. Ren, L. Cai, and K. Zhu, "Downlink scheduler for delay guaranteed services using deep reinforcement learning," *IEEE Transactions on Mobile Computing*, vol. 23, no. 4, pp. 3376–3390, Apr. 2024, doi: 10.1109/TMC.2023.3276697.
- [22] X. Wang, Y. Wang, J. Zhao, C. Weng, Y. Yan, and Z. Li, "Joint long-term user scheduling and beamforming design for burst IIoT," *IEEE Internet of Things Journal*, vol. 11, no. 12, pp. 22628–22642, Jun. 2024, doi: 10.1109/IJOT.2024.3382738.
- [23] Z. Tao, W. Xu, and X. You, "Digital twin-accelerated online deep reinforcement learning for admission control in sliced communication networks," *IEEE Transactions on Communications*, vol. 73, no. 4, pp. 2490–2504, 2025, doi: 10.1109/TCOMM.2024.3476430.
- [24] Q. Tang and M. Bavaghar, "Link adaptation and multi-objective resource optimization in intelligent wireless networks using power-domain non-orthogonal multiple access," *Ain Shams Engineering Journal*, vol. 16, no. 4, Mar. 2025, doi: 10.1016/j.asej.2025.103331.
- [25] S. O. Adebayo, A. Barnawi, T. Sheltami, and M. Felemban, "Dynamic spectrum sharing in heterogeneous wireless networks using deep reinforcement learning," *Internet of Things*, vol. 32, Jul. 2025, doi: 10.1016/j.iot.2025.101635.
- [26] A. B. A. Gowda, N. V. Babu, N. Anughna, and J. J. Jijesh, "A comprehensive survey on subspace-based direction of arrival estimation algorithms: performance, accuracy and complexity analysis," in *2025 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, Apr. 2025, pp. 1–7, doi: 10.1109/ICKECS65700.2025.11035231.
- [27] S. Denno, A. Yamada, and Y. Hou, "Practical uplink multi-user MIMO scheduling based on iterative heuristic search," *IEICE Transactions on Communications*, vol. E108-B, no. 5, pp. 665–672, May 2025, doi: 10.23919/transcom.2024EBP3119.
- [28] S. Kurma, K. Singh, P. K. Sharma, C.-P. Li, and T. A. Tsiftsis, "On the performance analysis of full-duplex cell-free massive MIMO with user mobility and imperfect CSI," *IEEE Transactions on Communications*, vol. 73, no. 5, pp. 3683–3701, May 2025, doi: 10.1109/TCOMM.2024.3490503.
- [29] J. Xu *et al.*, "Joint AP scheduling and power allocation based on synergistic DRL for cell-free massive MIMO," *IEEE Communications Letters*, vol. 29, no. 5, pp. 1082–1086, May 2025, doi: 10.1109/LCOMM.2025.3554179.
- [30] C.-W. Cho and M.-S. Pan, "Resource scheduling in MU-MIMO and NOMA enabled integrated access and backhaul networks," *IEEE Open Journal of the Communications Society*, vol. 6, pp. 551–559, 2025, doi: 10.1109/OJCOMS.2025.3525506.
- [31] Z. Shu *et al.*, "Decoupled uplink-downlink multi-connectivity scheduling in full-duplex cell-free massive MIMO networks: a HGN-DRL approach," *IEEE Transactions on Networking*, vol. 33, no. 5, pp. 2367–2382, Oct. 2025, doi: 10.1109/TON.2025.3561048.
- [32] A. Ichkov, A. Wietfeld, M. Petrova, and L. Simić, "HBF MU-MIMO with interference-aware beam pair link allocation for beyond-5G mm-Wave Networks," *IEEE Transactions on Mobile Computing*, vol. 24, no. 5, pp. 4248–4262, May 2025, doi: 10.1109/TMC.2025.3526547.
- [33] N. Gadde, R. Shivaswamy, R. B. H. Siddamal, G. Gowrishankar, G. T. Raju, and S. S. P. Vijay, "Hybrid resource optimization strategy in heterogeneous wireless networks," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 37, no. 2, Feb. 2025, doi: 10.11591/ijeecs.v37.i2.pp829-838.
- [34] A. Mahmood, S. Khan, S. Hussain, and M. Zeeshan, "Performance analysis of multi-user downlink PD-NOMA under SUI fading channel models," *IEEE Access*, vol. 9, pp. 52851–52859, 2021, doi: 10.1109/ACCESS.2021.3070147.

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