DTPRA: Dynamic Traffic and Priority-Aware Resource Allocation with Admission Control in Highly Dense Heterogeneous Wireless Networks

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Received: 24 April 2025 | Revised: 29 June 2025 | Accepted: 9 July 2025

DOI: https://doi.org/10.48084/etasr.11694

ABSTRACT

This study addresses the pressing challenges of next-generation Heterogeneous Wireless Networks (HWNs), specifically the need for higher spectral efficiency, reduced latency, increased throughput, and faster data transmission. With the growth of wireless technology, HWNs are becoming increasingly dense, and achieving seamless connectivity, optimal resource allocation, and ideal admission control mechanisms is crucial for enhancing HWN performance and expanding overall coverage. The complex interference issues associated with urban mobility make resource allocation and admission control extremely challenging, thereby increasing network complexity. Recently, soft-computing techniques such as Machine Learning (ML) and Deep Reinforcement Learning (DRL) have been applied to resource allocation and admission control to improve throughput and enhance spectral efficiency, thereby meeting users' application demands. This paper presents a Dynamic Traffic Priority-aware Resource Allocation (DTPRA) strategy. DTPRA introduces a throughput-gain model that incorporates an interference-optimization model by integrating backoff-time optimization into the resource allocation algorithm. This model then optimizes resource allocation for call admission according to user priority requirements using the Optimized DRL (ODRL) model. The DTPRA-ODRL approach is effective in reducing resource access failure and delay, with higher throughput and delivery ratios, thereby improving resource access efficiency compared to current Efficient Resource Allocation Admission Control based on DRL (ERAAC-DRL) methods.

Keywords-Dynamic Traffic Priority-aware Resource Allocation (DTPRA); Deep Reinforcement Learning (DRL); Machine Learning (ML); Efficient Resource Allocation Admission Control based on DRL (ERAAC-DRL); Heterogeneous Wireless Networks (HWNs)

I. INTRODUCTION

The development of fifth- and sixth-generation (5G and 6G) wireless networks has brought forth the need for high-performance communication infrastructures capable of supporting complex application service provisioning with minimal latency, enhanced reliability, and massive device connectivity [1]. As network density and user demands grow, resource management becomes increasingly challenging in highly heterogeneous and dynamic wireless environments. Traditional resource allocation techniques have generally relied on static decision-making processes, assuming fixed user mobility and pre-determined traffic behavior [2]. Such assumptions are inadequate for modern, high-mobility use cases involving fast-fading scenarios, such as communication on high-speed trains and vehicles.

Dynamic wireless systems introduce frequent variations in signal strength, complex interference patterns, and unpredictable channel behavior. These characteristics severely impact admission control and resource allocation strategies [3]. Addressing these challenges has led to the integration of Multi-User Multiple-Input Multiple-Output (MU-MIMO) systems into next-generation wireless networks. MU-MIMO enhances spectral efficiency and improves Quality of Service (QoS) by enabling simultaneous data transmissions across multiple users [4, 5]. It is particularly effective in mitigating the effects of fast-fading environments and supports stable, high-throughput connectivity under variable channel conditions [6].

Conventional resource management and call admission control in heterogeneous wireless networks often assume quasi-static user behavior [6]. These models typically rely on periodic or pre-configured strategies for resource allocation, which are effective only in stable conditions. They fail to meet the demands of emerging applications that require low-latency responses and adaptability to user mobility and rapidly changing traffic patterns.

In high-mobility environments, issues such as rapid signal degradation, Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) interference, and dynamic user locations introduce new challenges for maintaining service continuity and performance [7, 8]. To overcome these issues, a Dynamic Traffic Priority-aware Resource Allocation (DTPRA) strategy is proposed, integrated with admission control mechanisms. This approach dynamically adjusts resource allocation based on user service requests, traffic type, and network conditions. The model leverages Deep Reinforcement Learning (DRL) and online policy learning to make real-time decisions that optimize frequency slot assignment and admission control. The goal is to maximize throughput while minimizing access failures and maintaining low latency in highly dynamic environments [9].

Recent research has explored various approaches for resource allocation and admission control in heterogeneous 5G and 6G networks employing Machine Learning (ML) models [10]. A study developed a mathematical model of Bit Error Rate (BER) performance in Sparse-Coding Multiple Access with Orthogonal Frequency-Division Multiplexing (SCMA-OFDM), incorporating the effects of Carrier Frequency Offset (CFO), and highlighting degradation under frequency misalignments [11]. A deep-learning-based framework was introduced for relay node placement and selection in multicellular networks, improving throughput and energy efficiency through dynamic topology adaptation. However, complexity posed limitations for resource-constrained deployments [12].

A hybrid model combining 5G millimeter-Wave (mmWave) and Dedicated Short-Range Communications (DSRC) for vehicular communication has demonstrated enhanced reliability and low latency under high-speed conditions [13]. User association in 5G networks was also improved using a Dueling Double Deep Q-Network (Dueling-DDQN) model, which enhanced decision efficiency and throughput [14], although computational costs remained a challenge. Decentralized multi-agent DRL was further explored for Vehicle-to-Everything (V2X) scenarios to achieve efficient resource utilization and delay reduction across heterogeneous traffic types [15].

Clustering-based learning for resource management in 5G heterogeneous networks has improved energy and spectral efficiency, but it requires accurate prior knowledge of user requirements [16]. A cross-layer resource allocation method that leverages environmental awareness effectively adapts to high-speed network conditions but introduces high computational complexity [17]. In massive MIMO environments, underlay spectrum-sharing models have been employed to enhance energy efficiency and spectral utilization, although static user assumptions have limited their effectiveness in mobile scenarios [18].

Hierarchical DRL techniques were employed for joint admission control and resource allocation in virtual network embedding, thereby improving latency and resource utilization [19]. A DRL scheduler was designed to provide strict delay guarantees for 5G services, offering significant delay reductions [20]. For Industrial Internet of Things (IIoT) scenarios, long-term optimization techniques for user scheduling and beamforming enhanced energy efficiency and system capacity, although uplink dynamics were not fully considered [21].

In 5G Radio Access Networks (RANs) and Mobile Edge Cloud (MEC) environments, slicing and admission control frameworks have been introduced to ensure resource isolation and service reliability across diverse use cases [22]. Digital Twin (DT) technology was employed to accelerate online DRL-based admission control in sliced networks, enhancing convergence and performance [23]. However, dependency on accurate DTs may hinder scalability in real-world conditions.

Despite these advancements, many DRL-based strategies fail to address extreme interference conditions and varying propagation losses in highly dynamic environments [16-18], often resulting in resource access failures [19, 20] and reduced throughput and spectrum utilization [21-23]. The proposed DTPRA model overcomes these limitations by introducing an adaptive, throughput-optimized framework for resource allocation and admission control. By integrating user-service-priority awareness and online learning, the model ensures efficient real-time decision-making in heterogeneous network conditions [24]. The key contributions of this work are summarized as follows:

- Introduction of a throughput-gain-aware resource allocation framework tailored to dynamic environments.
- Integration of failure minimization techniques into the resource allocation model.
- Deployment of user-service-priority-aware call admission control using DRL.
- Design of an optimized online policy learning mechanism to improve learning adaptability and resource assignment performance.
- Simulation results demonstrate that the proposed DTPRA-Optimized DRL (DTPRA-ODRL) model achieves higher throughput, better delivery ratios, reduced access failures, and lower latency compared to existing methods.

II. PROPOSED METHODOLOGY

This section introduces a dynamic traffic-aware resource allocation design to improve the overall QoS of MU-MIMO networks. The work first introduces the system model used for resource allocation and admission control strategy; then presents a mathematical model of throughput gain and an algorithm for initial resource allocation. Next, the work introduces an optimization algorithm to allocate resources with an admission control policy using an ODRL model. The ODRL-based model aids in satisfying users' service priority requirements in MU-MIMO. The optimized resource allocation model achieves faster convergence, thereby improving MU-MIMO network performance, including enhanced throughput, reduced access failures, and improved spectral efficiency.

A. Dynamic Traffic Priority-Aware Resource Allocation Admission Control Metric Model

This section presents the DTPRA approach for maximizing throughput in MU-MIMO 5G networks. Let the IoT node x throughput be denoted as S_x and the resource selected for x be defined as e_{xy}, where y denotes the set of available resources. When a resource is not selected for an IoT node x, $e_{xy} = 0$; when the resource is selected, $e_{xy} = 1$. Using this, the total throughput gain of the IoT node x can be denoted as:

$$max \sum_{x=1}^{R} S_x \tag{1}$$

subject to the constraint:

$$\sum_{x=1}^{R} e_{xy} = 1, \quad \forall y \tag{2}$$

where R denotes the total number of IoT nodes in the network X. The throughput gain S_x for node x is calculated using the set of resources V_x and the access probabilities l_{xy}. Here, l_{xy} denotes the likelihood that node x can successfully access resource y, assumed to be independent of other nodes. Using this, the throughput gain is expressed as:

$$S_x = 1 - \prod_{y \in V_x} l'_{xy} = 1 - \prod_{y=1}^{T} \left(l'_{xy}\right)^{e_{xy}} \tag{3}$$

In (3), $l'_{xy} = 1 - l_{xy}$ represents the probability that node x cannot access y, and $1 - \prod_{y \in V_x} l'_{xy}$ represents the probability that node x can access at least one resource in V_x. In a typical MU-MIMO 5G network, x usually accesses a single y; hence, for this scenario, $S_x = 1$.

Equation (2) may not always be strictly satisfied for distributed resource-selection methods. Moreover, the constraint set in (1) and (2) corresponds to Non-deterministic Polynomial Time (NP) and non-linear integer problems, which are computationally challenging. To address this, the DTPRA approach is used to handle the constraints effectively.

Consider x using multiple spectrums denoted as T for a given resource y. In a normal MU-MIMO 5G network scenario, x can access only one y; thus, only one spectrum T is utilized for data transmission. For efficient communication, x performs a sensing operation on y during each cycle to determine available resources. Time is divided into fixed cycle durations, and the DTPRA approach assumes error-free, ideal sensing.

For every node x, assume $V_x \cap V_y = \emptyset$ for $x \neq y$. The constraint in (2) facilitates better throughput gain by selecting efficient resources. To evaluate whether resources are selected efficiently, the throughput gain is calculated as:

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

$$\begin{aligned} \delta S_x &= S_x^z - S_x^q \\ &= \left[1 - \left(1 - l_{xy'_x}\right) \prod_{y \in V_x} \left(1 - l_{xy}\right)\right] - \\ &\quad \left[1 - \prod_{y \in V_x} \left(1 - l_{xy}\right)\right] \\ &= l_{xy'_x} \prod_{y \in V_x} \left(1 - l_{xy}\right) \end{aligned} \tag{5}$$

Here, δS_x represents the additional throughput gain achieved by efficiently allocating resource y'_x. As V_x increases, δS_x decreases, converging toward zero.

When considering multi-user resource allocation under priority-aware admission control, the standard resource allocation-aware call admission mechanism introduces overhead, as it must select effective resources for a particular contention window denoted as A. Therefore, an approach is required that selects resources efficiently without affecting throughput gain and while reducing computation complexity. For this scenario, the DTPRA approach first uses (5) for evaluating δS_x for a given x, then manages resource-selection for multiple users by sharing resources that have been selected by other x, and optimizes overall throughput using (1). Since evaluating throughput gain multiple times creates computational complexity, throughput gain is only evaluated during resource-selection by considering overhead factor D, where $D < 1$. The value of D in DTPRA depends on the shared resources quotient across all x. Equation (6) models D by considering a given contention window A.

Let h be the backoff parameter, representing the mean value of the backoff range that each x can select. In the DTPRA approach, h is initially set to 0 or lies in the $[0, A - 1]$, giving the mean value $h = (A - 1)/2$. The mean overhead is then evaluated using (6):

$$D(A) = \frac{\left(\frac{[A-1]\varphi}{2} + s_{Par1} + s_{Par2} + s_{Par3} + s_{Par4} + 3s_{Par5}\right)}{s_I} \tag{6}$$

In (6), s_{Par1} denotes the sensing-time of x, s_{Par2} denotes packet-synchronization size, s_{Par3} denotes the request-to-send parameter, s_{Par4} denotes ready-to-send, s_{Par5} denotes propagation-delay duration, S_I denotes cycle-time, and φ denotes the duration corresponding to a single h. The complete process of resource allocation with admission control is described in Algorithm 1.

```
Algorithm 1. Resource allocation with admission control
Start
Input available channels $V_z = \{1,2,3,\dots,T\}$ and initialize $V_x = \emptyset$ for each node $x = 1,2,\dots,R$
For each $x = 1$ to $R$:
    $y'_x = \underset{y \in V_z}{argmax}\, l_{x,y}$
    If $V_x = \emptyset$, compute $\delta S_x$ using (5)
    Else, $\delta S_x = l_{xy'_x}$
End for
```

```
8.  $x' = \underset{x}{\operatorname{argmax}}\, \delta S_x$
9.  Allocate channel $y'_{x'}$ to node $x'$
10. Update $V_z = V_z \setminus \{y'_{x'}\}$
11. If $V_z$ is empty, terminate the process;
    else, return to step 3
12. Stop
```

B. Deep Reinforcement Learning Model for Resource Allocation Optimization

This section introduces an ODRL approach for resource allocation according to users' QoS and priority requirements. ODRL first computes learning agents utilizing the Q-tables defined as $Q(state, action)$, where $state$ represents the network state and $action$ represents the action selected for each learning agent. The Q-table is updated dynamically over multiple iterations using (7):

$$Q(state^T, action^T) = Q(state^T, action^T) + \partial * \begin{pmatrix} IO_K^T + \gamma * Q(state^{T+1}, action^{T+1}) \\ -Q(state^T, action^T) \end{pmatrix} \tag{7}$$

In (7), ∂ denotes the learning rate of the agent, IO_K^T defines the reward function (ranging from 0 to 1) based on distributed user service requests at iteration T. The model assumes K user's service requests, expressed in (8), and n frequency slots expressed in (9):

$$T^K = \{T^1, T^2, \dots, T^K\} \tag{8}$$

$$V^n = \{V^1, V^2, \dots, V^n\} \tag{9}$$

Each service request obtained through mobile nodes is communicated to MU-MIMO networks, where the system identifies service dependencies, priorities, and required frequency slots. Based on these factors, frequency slots are allocated according to users' priority levels. After resource optimization, admission control is performed by combining the allocation with the ODRL strategy, thereby improving resource allocation efficiency and reducing access failures. The core objective of ODRL in resource allocation and call admission control is to maximize throughput gain while minimizing resource access failure. The service-request execution procedure is carried out in frequency slots, represented as:

$$action^T = \{V^1, V^2, \dots, V^n\} \tag{10}$$

In state-space operation, the states of the users' service requests and frequency slots are calculated. Let's consider the user's service request T arrives dynamically at time t_i. The corresponding state is given by (11):

$$state_{t_i}^T = state_{t_i}^{T^K} \cup state_{t_i,V^n}^{T^K}\} \tag{11}$$

where $state_{t_i}^{T^K}$ represents the state of service request T^K at time t_i, and $state_{t_i,V^n}^{T^K}$ represents the state of the same request across the frequency slots V^n. This can be detailed as:

$$state_{t_i}^T = \left[T_{priority}^K, V_{priority}^n, U^K, Q^K\right] \tag{12}$$

where $T_{priority}^K$ is the ratio of the users' service-request size to available resources, $V_{priority}^n$ is the ratio of the resource consumption rate of frequency slots to the overall network consumption rate, U^K denotes the total time duration for request handling, and Q^K denotes resource utilization. Using (10), (11), and (12), the ODRL reward function is expressed as:

$$IO_K^T = \min(U^K, Q^K) \tag{13}$$

The complete process of resource allocation using ODRL is given in Algorithm 2.

```
Algorithm 2: ODRL-based resource
allocation admission control strategy
Input:  User requests $T^K = \{T^1, T^2, \dots, T^K\}$,
        frequency slots $V^n = \{V^1, V^2, \dots, V^K\}$,
        channels $H_1 = \{H_1, H_2, \dots, H_n\}$,
        MU-MIMO networks $D^J = \{D^1, D^2, \dots, D^J\}$
Output: Mapping of $T^K$ to the frequency slot
        $V^n$, creating a resource allocation
        schedule with maximum throughput
        and minimum access failure
1.  Initiate $\beta$, $m\delta$, $b\delta$, to 0 and assign
    $Q(State^T, Action^T) \leftarrow 0$
2.  For each batch-iteration $b\delta$:
3.     Determine $state^T$
4.     Evaluate service-dependencies and
       throughput using Algorithm 1
5.     Evaluate $T_{priority}^K$
6.     Evaluate $V_{priority}^n$
7.     For each step within the batch:
8.        Check resource availability based
          on service dependency, $T_{priority}^K$ and
          $V_{priority}^n$
9.        Determine $action^T$
10.       If $\gamma \neq 0$:
11.          Select a frequency slot using
             likelihood $\beta$
12.       Else
13.          Evaluate argmax $Q\left(state_{t_i}^T, action^T\right)$
14.       End if
15.       Evaluate reward-function $IO_K^T$ using
          (7)
16.       Check whether reward is positive
          or negative based on throughput
          gain and packet-failure rate.
17.       If objective parameters are
          optimized:
18.          Select the best positive
             incentive from the ODRL Q-table
19.          Allocate frequency slot for the
             respective service using (13)
20.          Update $state^T$ to $state^{T+1}$
21.       Else
22.          Repeat until the last iteration
             is reached.
23.       End if
24.    End for
25. End for
```

The ODRL strategy uses parameters such as likelihood β, iteration batch size $b\delta$, replay-memory $m\delta$, and storage memory δ. Each action is represented as $(action^T, state^T, IO_K^T, state^{T+1})$. When a new service request T arrives, ODRL determines its dependencies, assigns priority, and allocates frequency slots accordingly. The best-rewarding outcomes from (13) are used to update the Q-table through (7). This process reduces computational overhead, minimizes access failures, and maximizes throughput gain.

III. RESULTS AND DISCUSSION

This section presents the simulation study of the proposed model, DTPRA-ODRL. It compares its performance with that of the existing system, Efficient Resource Allocation and Admission Control using DRL (ERAAC-DRL), as described in [20] and [23]. The NS3-based SIMITS simulator [25] is utilized for the simulation study, in which both DTPRA-ODRL and ERAAC-DRL are implemented. The scenarios are created using Deep MIMO [13] to resemble a realistic mobility model, considering the SUI channel fading model obtained from the NYUSIM library [26]. The simulation parameters are consistent with those presented in [20]. The parameter includes QAM-18 with a 28 GHz frequency capable of producing a 100 MHz bandwidth, with a 400 m cellular radius, considering 46 dBm base station power. The simulation is conducted by varying the number of nodes between 25 and 50, with 20 iterations. The metrics used in the simulation study are throughput, resource access failure, and resource access success, all of which are evaluated under varying node sizes.

A. *Throughput Performance*

The throughput performance is measured in terms of bits/Hz/s by varying the mobile node size from 25 to 50, considering 20 iterations. Achieving a higher throughput enables the model to transmit a greater number of packets in HWNs; a higher throughput value indicates better model performance. Figure 1 shows the throughput achieved using ERAAC-DRL and DTPRA-ODRL for 25 mobile nodes. The results show that an average improvement of 23.39% is achieved using DTPRA-ODRL over ERAAC-DRL. Similarly, Figure 2 shows the throughput achieved for 50 mobile nodes. The results show that an average improvement of 14.13% is achieved using DTPRA-ODRL over ERAAC-DRL. A significant throughput enhancement is observed due to the resource optimization performed to maximize the throughput gain of (1), as outlined in Algorithm 1.

B. *Resource Access Failure Performance*

The resource access failure is measured as admission control failures during spectrum sensing and communication for 25 and 50 nodes over 20 iterations. Achieving a lower failure value enables the model to provide more efficient spectrum usage, thereby enhancing the quality of experience in HWNs; a lower failure value indicates better model performance. Figure 3 illustrates the resource access failure using ERAAC-DRL and DTPRA-ODRL for 25 mobile nodes. The results show that an average failure reduction of 75.73% is achieved using DTPRA-ODRL over ERAAC-DRL. Similarly, Figure 4 shows the resource access failure for 50 mobile nodes. The results show that an average failure reduction of 32.03% is achieved using DTPRA-ODRL compared to ERAAC-DRL. A significant decrease in resource access failure is observed due to the enhanced backoff optimization model introduced in (6) and the resource optimization performed using (5) in Algorithm 1.

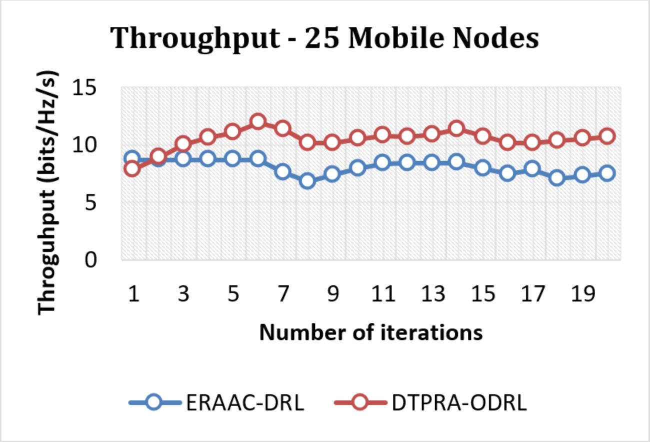

Fig. 1. User throughput of DTPRA-ODRL and ERAAC-DRL for 25 mobile nodes.

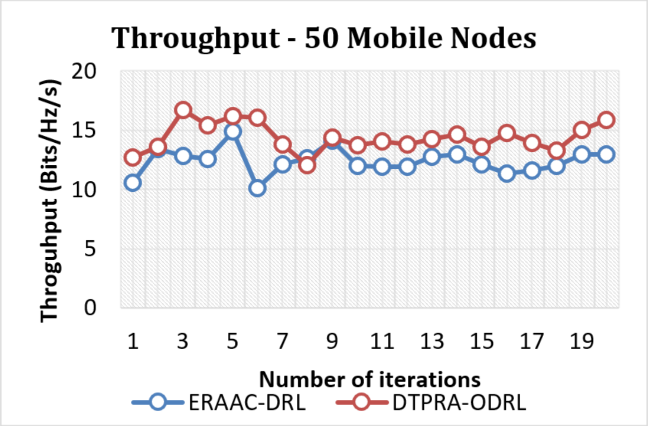

Fig. 2. User throughput of DTPRA-ODRL and ERAAC-DRL for 50 mobile nodes.

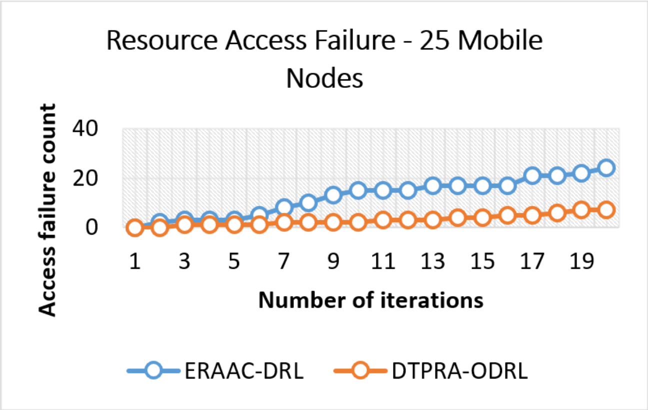

Fig. 3. Resource access failure of DTPRA-ODRL and ERAAC-DRL for 25 mobile nodes.

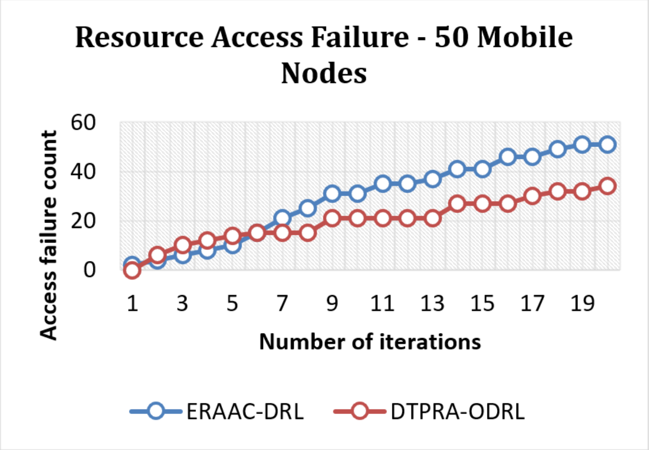

Fig. 4. Resource access failure of DTPRA-ODRL and ERAAC-DRL for 50 mobile nodes.

C. Resource Access Success Performance

The resource access success performance is measured in terms of how resource access and admission control are successfully implemented during the spectrum sensing and communication process, considering varied mobile node sizes of 25 and 50, with 20 iterations. Attaining a higher success rate enables the model to provide improved spectrum efficiency, thereby enhancing network performance and users' quality of experience in HWNs. A higher success value indicates better model performance. Figure 5 shows the resource access success using ERAAC-DRL and DTPRA-ODRL for 25 mobile nodes. The results show that an average success improvement of 26.78% is achieved using DTPRA-ODRL over ERAAC-DRL. Similarly, Figure 6 shows the resource access success for 50 mobile nodes. The results show that an average success enhancement of 24.44% is achieved using DTPRA-ODRL over ERAAC-DRL. The significant resource access success improvement is attributed to the optimization of throughput gain in (1), combined with the enhanced backoff optimization model introduced in (6) and the resource optimization performed using (5) in Algorithm 1. The optimal solution with call admission is then performed using ODRL in Algorithm 2.

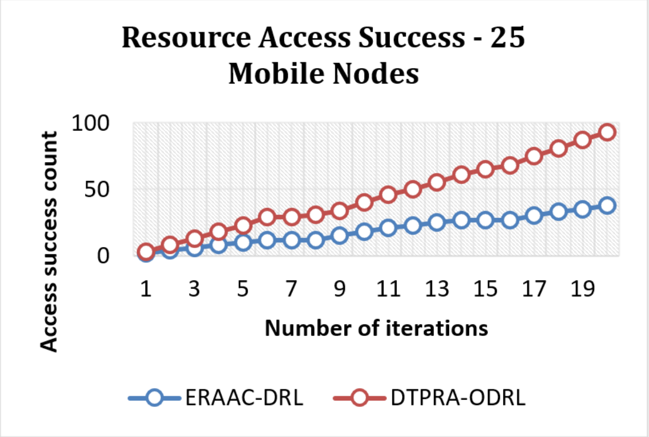

Fig. 5. Resource access success of DTPRA-ODRL and ERAAC-DRL for 25 mobile nodes.

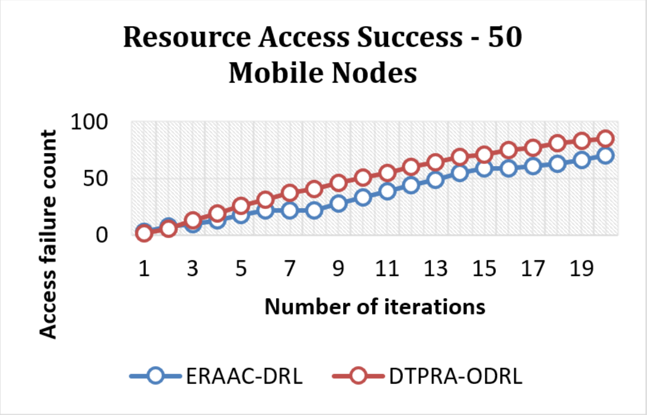

Fig. 6. Resource access success of DTPRA-ODRL and ERAAC-DRL for 50 mobile nodes.

D. Delay and Delivery Ratio Performance

The delay performance is evaluated in terms of total time measured in seconds, with the mobile node size varied between 25 and 50. A lower delay value indicates improved performance in HWNs, as it implies that data packets are transmitted and received more quickly with reduced waiting times. Figure 7 illustrates that the proposed DTPRA-ODRL model achieves a notable 45.07% reduction in delay compared to the ERAAC-DRL model.

The delivery ratio performance is assessed as the ratio of total packets successfully delivered to the total number of packets transmitted, also under varying mobile node sizes of 25 and 50. A higher delivery ratio indicates better performance in HWNs. As shown in Figure 8, the proposed DTPRA-ODRL model improves the delivery ratio by 25.91% compared to the ERAAC-DRL model.

This significant improvement in both delay reduction and delivery ratio enhancement can be attributed to the faster convergence properties of the ODRL model, combined with the shared resource-based optimization mechanisms embedded in the proposed strategy. These mechanisms ensure that service requests are executed efficiently across varying conditions.

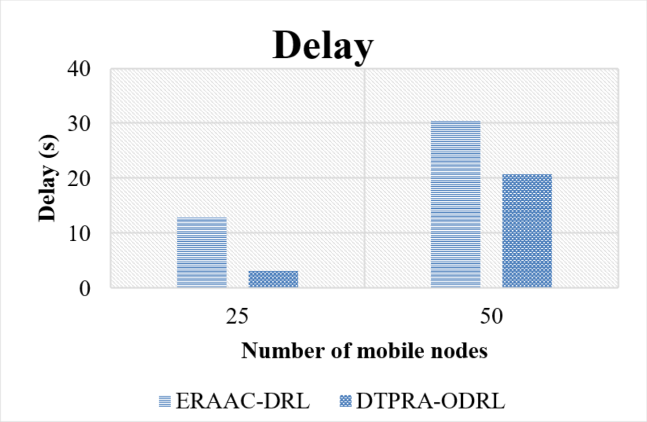

Fig. 7. Delay performance of DTPRA-ODRL and ERAAC-DRL under varied mobile node sizes.

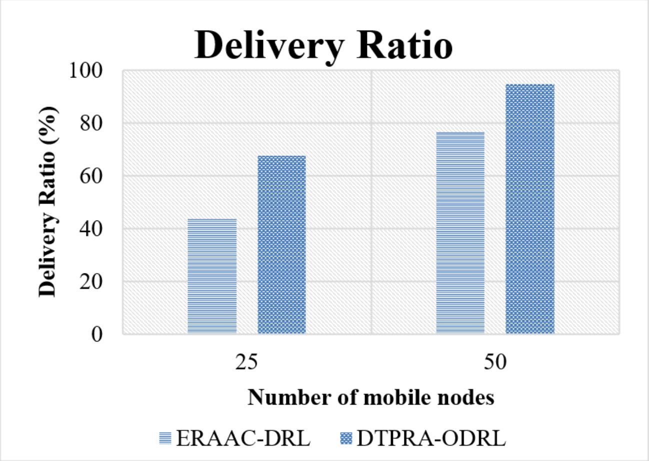

Fig. 8. Delivery ratio performance of DTPRA-ODRL and ERAAC-DRL under varied mobile node sizes.

E. Comparative Study

This section presents a comparative study of different resource allocation and admission control methodologies, summarized in Table I. Three models employing DRL-based optimization are considered. Table I shows that the work presented in [20] improves user Quality of Experience (QoE) by 15% for IIoT burst traffic; however, the computational process involves high complexity. The work presented in [21] demonstrates low-latency service delivery with an 18% reduction in delay, but its performance is impacted when applied in highly dense HWNs. Authors in [23] improved QoS by 20% based on the success rate. However, significant interference and computation complexity affect the model's performance. In contrast, the proposed DTPRA-ODRL model reduces access failure, improves the success rate, and enhances throughput, achieving a 25% improvement in spectral efficiency compared to [23]. Overall, QoS and QoE efficiency are also improved. These results indicate that the proposed model outperforms other state-of-the-art DRL-based models.

TABLE I. COMPARATIVE STUDY OF DIFFERENT DRL-BASED RESOURCE ALLOCATION AND ADMISSION CONTROL MODELS

Method	Network	Optimization strategy	Metrics optimized	Limitation	Performance improvement
[21]	IIoT over 6G networks	Long-term joint DRL	Beamforming efficiency, user QoE	Relatively high complexity in bursty IoT traffic management	15% QoE improvement for bursty traffic scenarios
[20]	LTE/5G networks	DRL-based scheduling	Delay, system throughput	Limited adaptability to heterogeneous networks	18% reduction in service delay
[23]	Sliced 6G networks	Online DRL with DT	Admission success rate, QoS	High computational complexity for DT operations	20% improvement in QoS
DTPRA-ODRL (proposed)	Heterogeneous MU-MIMU networks	ODRL	Throughput gain, backoff, service priority	Needs further evaluation under different propagation scenarios	25% improvement in spectral efficiency, enhancing both QoS and QoE

IV. CONCLUSION

The study analyzed various soft-computing-based resource allocation and admission control optimization models for Heterogeneous Wireless Networks (HWNs). The analysis shows that existing models induce higher complexity, fail to provide service priority with efficient spectrum usage, and result in increased access failure due to interference. This research introduces the Dynamic Traffic Priority-aware Resource Allocation (DTPRA) strategy by modeling throughput gain with backoff-time optimization incorporated into the resource allocation algorithm. Subsequently, an Optimized Deep Reinforcement Learning (ODRL) model is employed to provide service-priority-aware and traffic-aware service provisioning.

The simulation study demonstrates that DTPRA-ODRL effectively reduces resource access failure, decreases delay, and improves the resource access success rate, delivery ratio, and overall throughput compared to existing methods, namely Efficient Resource Allocation and Admission Control using Deep Reinforcement Learning (ERAAC-DRL), in complex urban propagation environments. A comparative study further evaluates the proposed model against current state-of-the-art resource allocation and admission control strategies, confirming its superior performance.

Future work will focus on further optimizing link scheduling to reduce packet loss and developing a more dynamic link-scheduling algorithm to achieve enhanced performance under increasingly complex propagation scenarios.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, we extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process. No funding was received for this research.

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