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Adaptive Q-Learning-Based Radio Resource Management Optimization in 5G and Beyond Heterogeneous-heterogeneous Networks: A Comprehensive Review

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Abstract

This paper reviews advanced radio resource management (RRM) optimization techniques in 5G and beyond heterogeneous-heterogeneous networks (Het-HetNets). Key innovations include fairness-aware models for mmWave 5G, machine learning (ML)-driven traffic management, and game-theoretic approaches for interference mitigation in Massive MIMO systems. Blockchain technology emerges as a promising tool for secure spectrum sharing, while deep learning enhances handover management and resource allocation. Hybrid frameworks, such as deep reinforcement learning and non-orthogonal multiple access, address energy efficiency and quality of service (QoS) challenges for IoT, autonomous vehicles, and smart cities. Despite these advancements, challenges like scalability, computational complexity, and data privacy persist. Q-learning-based adaptive RRM frameworks demonstrate potential for optimizing energy and spectral efficiency by addressing dynamic network conditions. The integration of ML with blockchain enables secure and decentralized RRM. Critical research gaps identified include scalability, real-time deployment, and interference management in ultra-dense networks. This review highlights the importance of scalable, efficient, and adaptive solutions to advance the telecommunications system.

Keywords: RRM, Het-HetNets, ML, Q-Learning, 5G

Introduction

The fifth generation (5G) of wireless networks represents a significant advancement in terms of the services it offers, as well as the challenges it presents. Compared to 4G, 5G is expected to deliver about 100 times more capacity (10 Mbps per m2) and support 100 times more connected devices (106 connected devices per km2). It aims to achieve an end-to-end latency of less than 1 ms, which is crucial for applications that require minimal delays.

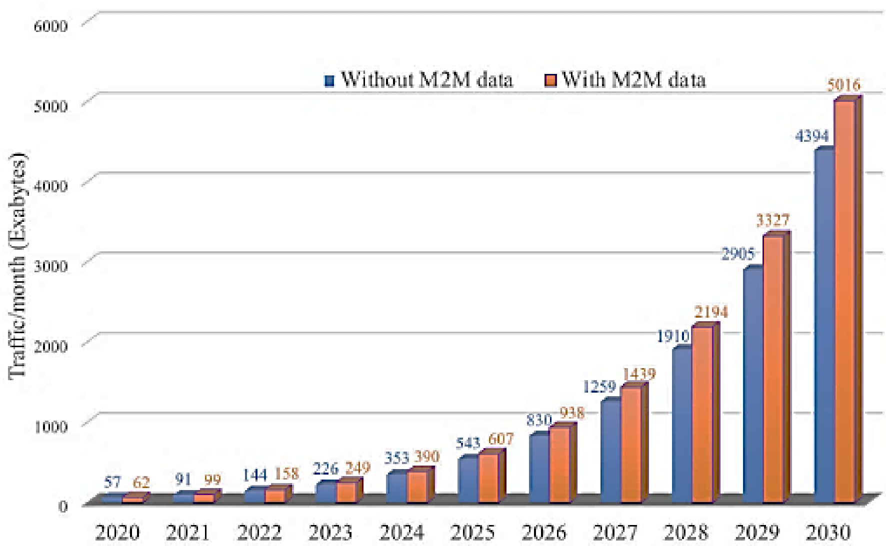

Figure 1: Global mobile data traffic forecast by ITU (Tariq et al., 2020)

With mobile subscriptions reaching 7.9 billion in 2020, and mobile data traffic increasing by 50%, projections estimate that there will be 8.8 billion subscriptions by the end of 2030, with 88% being mobile broadband connections. Users are expected to demand an average capacity of 25 gigabytes per month (Rony et al., 2021a).

The fifth generation (5G) mobile communication technology is designed to meet all communication needs. Heterogeneous networks (HetNets) are a new emerging network structure. HetNets have greater potential for radio resource reuse and better service quality than homogeneous networks since they can evolve small cells into macrocells (Luong et al., 2019; Yadav et al., 2021). However, despite the advantages, HetNets has not fully addressed challenges like co-tier and cross-tier interferences within the network structure. Cell densification is a cost-effective method to increase network capacity but faces challenges such as interference management. The deployment of small cells (SC) and techniques like enhanced Inter-Cell Interference Coordination (eICIC) address cost and interference challenges (Amine et al., 2020). The combination of widely deployed SCs and network-wide Internet of Things (IoT) devices leads to ultra-dense networks (UDN) requiring huge, aggregated capacity. Traditional techniques like carrier aggregation and frequency reuse (FR) face challenges due to poor frequency resource management (while some coverage areas are overprovisioned, others appear overloaded) (Rezaei & Ghahfarokhi, 2023; Zhihao et al., 2021a).

Heterogeneous-Heterogeneous Networks (Het-Hetnets)

The introduction of heterogeneous-heterogeneous networks (Het-HetNets) sometimes called multiple tiers of base stations is designed to eliminate cross-tier interference and minimize co-tier interference for network devices operating within the frequency spectrum. Het-HetNets encompass networks that combine various small cells, including Pico-cells eNodeBs (PeNBs) and next-generation NodeBs (gNBs) of 5G, into a single macro-cell (MeNB) utilizing diverse technologies and frequency spectrum (Agarwal et al., 2022a).

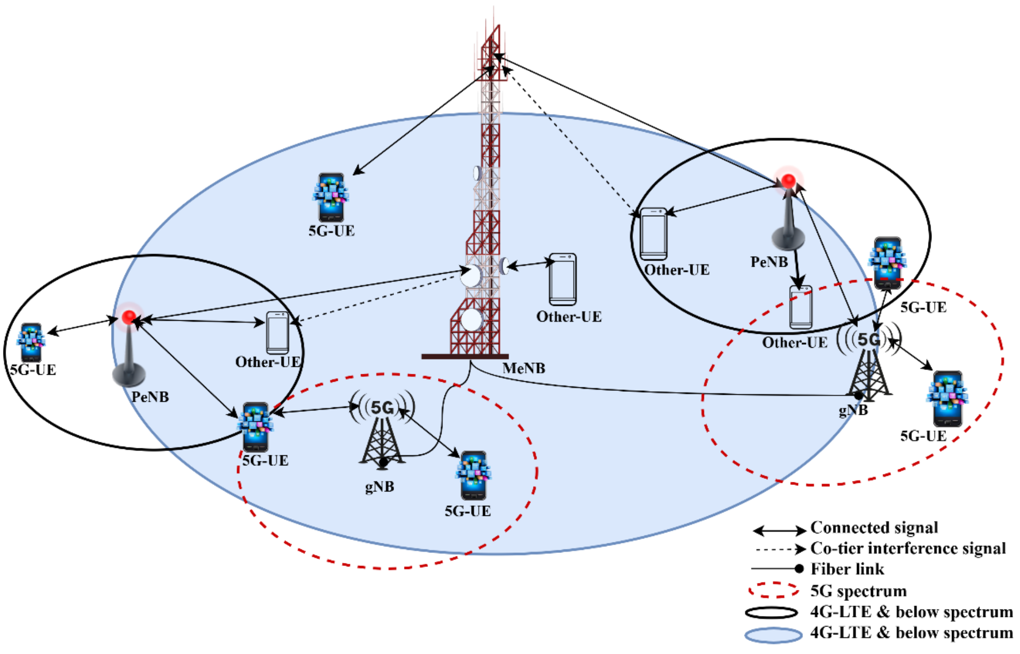

Figure 2: Proposed 5G and Beyond Het-HetNets System Model

The Het-HetNets model is expected to be deployed in urban areas where high traffic demand is required. This setup includes a MeNB with multiple associated small cells (PeNBs) operating within the 700 MHz to 3800 MHz spectrum bands, as well as gNBs (5G small cells) operating in the 3.5 GHz band (Jusoh, 2023). When deploying the Het-HetNets model in scenarios with high traffic demand, the number of other user equipment (other-UEs) often surpasses the number of 5G-enabled user equipment (5G UEs), primarily because many devices lack 5G compatibility. Consequently, a substantial number of other-UEs connect to MeNB due to its extensive network coverage and high received signal power (RSRP). This situation results in the over-utilization of the MeNB, leading to congestion, while the PeNBs remain under-utilized, despite having adequate resources allocated through dynamic spectrum sharing (DSS) from the gNBs.

However, the implementation of Het-HetNets presents significant challenges concerning network load balancing, resource sharing and allocation, and co-tier interference. Wireless networks are becoming more complex to meet the demands for high capacity, low latency, and global coverage, incorporating features such as Massive MIMO, Multi-RATs, CRAN, network slicing, edge computing, and NFV. The advancement of these 5G networks requires increased automation, as current networks lack flexibility in this area. Artificial Intelligence, particularly Machine Learning, can leverage the abundant data in modern mobile networks to help manage these complexities and enhance quality of service (QoS).(William et al., 2022).

The efficient allocation of radio resources, tailored to the varying demands of the network, is essential for optimizing the use of limited resources (Abbass et al., 2022). However, managing radio resources (RRM) in ultra-dense heterogeneous networks (HetNets) presents challenges due to interferences inherent in the multi-tier architecture and the dynamic conditions of the network. In 5G HetNets, interferences can be effectively addressed through a machine learning-based self-adaptive resource allocation scheme that integrates both independent and cooperative learning, specifically designed for ultra-dense 5G environments (Iqbal, Ansari, Akhtar, Rafiq, et al., 2023).

Interference mitigation in (Iqbal et al., 2021a) proposes a Q-learning-based adaptive resource allocation scheme for ultra-dense SCs HetNets. Results show significant improvements in mitigating co-tier and cross-tier interference, enhancing the quality of service (QoS) for both macrocell user equipment (MUEs) and small cell user equipment

(SUEs). The approach improves energy efficiency and spectral efficiency compared to traditional methods. In (Bartsiokas et al., 2023), presents a deep learning-based framework for optimizing relay node (RN) placement and selection in 5G/B5G multicellular networks. Key challenges include interference management, computational complexity, and real-time deployment. These highlight the need for adaptive radio resource management frameworks in 5G and beyond Het-HetNets, leveraging Q-learning techniques that minimize interference and improve both Energy Efficiency (EE) and Spectral Efficiency (SE), while ensuring scalability and performance reliability under changing network conditions, including high user density, mobility, and dynamic traffic patterns.

The research examines the optimization of adaptive Q-learning-based radio resource management (RRM) frameworks for 5G and beyond Het-Heterogeneous Networks (Het-HetNets). The subsequent sections cover an overview of RRM and its various classes, types of machine learning, and a comparative summary table of related studies. The paper concludes with a discussion on future directions and a final conclusion.

Radio Resource Management (RRM) and Machine Learning (ML) Techniques

Radio Resource Management (RRM): encompasses strategies and algorithms designed to optimize the use of radio resources in wireless networks, ensuring efficient network infrastructure utilization while minimizing interference and maximizing client capacity. Applicable to cellular networks, wireless local area networks, sensor systems, and radio broadcasting, RRM operates through continuous monitoring of network conditions, including traffic load, interference, noise levels, coverage, and nearby access points. Based on this data, it dynamically adjusts configurations such as channel selection and transmission power to reduce interference, balance user access, and enhance overall performance. Incorporating artificial intelligence (AI) can further refine RRM by enabling smarter analysis of radio frequency patterns, simplifying management, and improving connectivity (Hossain et al., 2017).

1. Classes of RRM

Radio resource management (RRM) in wireless networks can be categorized into two primary types: static and dynamic (Lan et al., 2021).

a. **Static RRM:** This approach involves manual or computer-aided planning of cells or radio networks. It is typically employed in traditional wireless systems, such as 1G and 2G cellular networks, as well as in wireless local area networks (WLANs).

b. **Dynamic RRM:** This method adaptively modifies radio network parameters to account for variations in traffic load, user mobility, and quality of service requirements. Dynamic RRM schemes can significantly enhance system spectral efficiency, often achieving improvements by an order of magnitude.

RRM (Radio Resource Management) algorithms enhance spectrum utilization while preserving quality of service (QoS). They oversee parameters such as bandwidth, transmission time slots, and modulation techniques (Guo, 2020). The functionalities of RRM can be divided into three primary procedures:

a. **Resource Monitoring:** This process collects information about user preferences and evaluates the condition of the wireless access networks.

b. **Decision Making:** This step entails making important decisions, including network selection and bandwidth allocation.

c. **Decision Enforcement:** This phase is responsible for implementing the decisions reached in the previous step.

Machine Learning (ML): is a discipline within artificial intelligence, defined as a collection of computational algorithms that enable systems to autonomously learn, generate outputs, and progressively improve through the analysis of data and resulting feedback (Ahmad et al., 2022). These algorithms are trained using input data, allowing them to perform specific tasks, produce desired outputs, and be applied effectively to practical scenarios, including real-world business applications. Machine learning algorithms find utility in addressing complex business problems such as regression, classification, forecasting, clustering, and association rule learning, among others(Mollel et al., 2021).

2. ML Types

Machine Learning algorithms can be broadly categorized into three primary types based on their underlying methodology and approach: Supervised Learning, Unsupervised Learning, and Reinforcement Learning (analytixlabs, 2021). In the subsequent sections, a detailed representation of each type of algorithm will be provided.

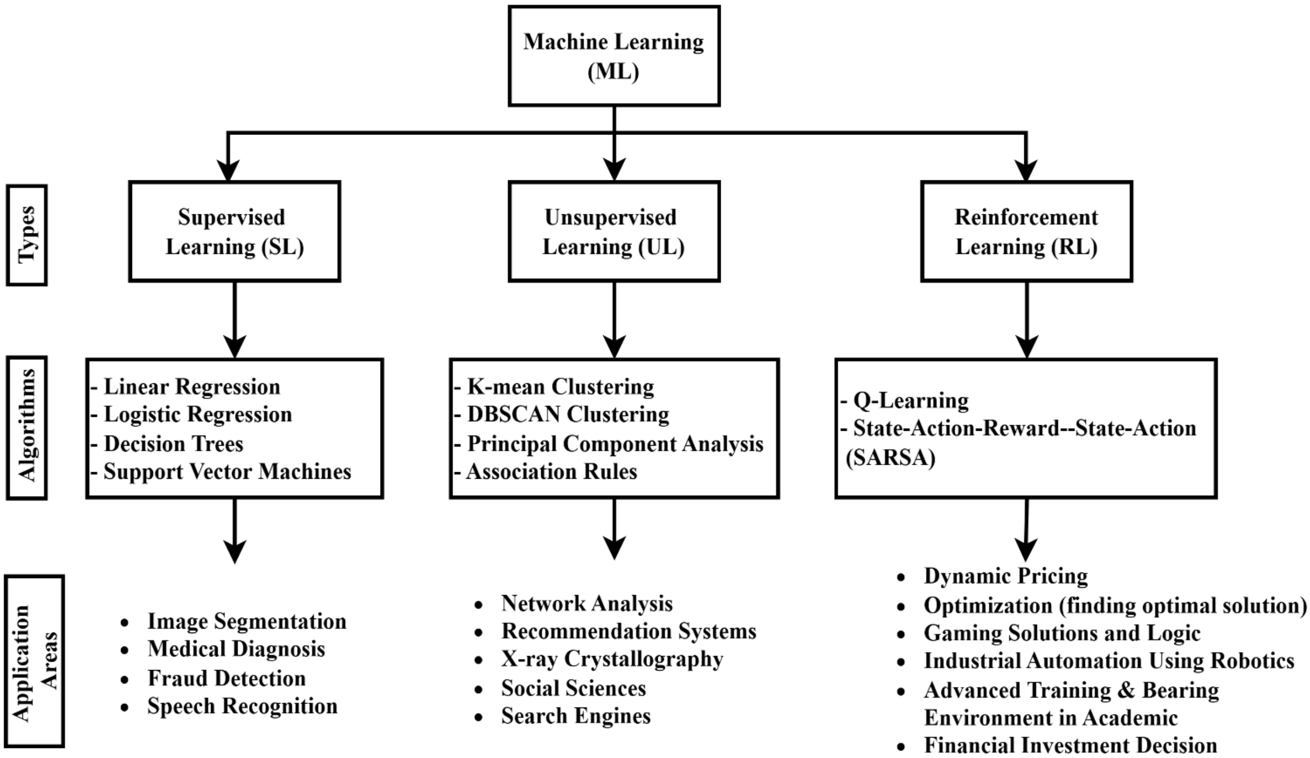

Figure 3: Machine Learning Structures

a. **Supervised learning (SL):** involves guidance from a supervisor who provides the desired outcomes for the system based on incoming data. This approach employs supervised algorithms to predict, estimate, or classify variables. The core concept of SL is to train a learning model to derive a generalized rule that maps inputs to outputs using examples of problems with known solutions. Once trained, the model can then identify optimal solutions for new, unseen samples (Kaur et al., 2021a).

SL techniques operate under the assumption that a dataset contains mappings between instances and their corresponding labels. Depending on the nature of the output data—continuous or discrete—SL can be categorized into two main tasks: regression and classification. For instance, classification learning algorithms include Bayes' theorem, K-nearest neighbors (K-NN), Naive Bayes (NB), and support vector machines (SVMs). Meanwhile, regression learning algorithms encompass methods such as artificial neural networks (ANNs) and generalized linear models (GLMs) (Gupta et al., 2022).

b. **Unsupervised learning (UL):** operates without predefined outcomes, aiming to uncover hidden patterns and structures in unlabelled data. It is widely applied for tasks like anomaly detection, pattern recognition, and dimensionality reduction (Gupta et al., 2022). Key models include:

   1) **Clustering**: Groups similar data points, with techniques like K-means, hierarchical, and fuzzy C-means.

   2) **Dimensionality Reduction**: Reduces data complexity using methods such as PCA and ICA, improving analysis and storage efficiency.

   3) **Density Estimation**: Encodes density information by modeling scenes directly and estimating density through response functions.

   These techniques enable efficient analysis and insights in diverse applications, from network clustering to data localization and anomaly detection.

c. **Reinforcement Learning (RL):** focuses on decision-making and identifying optimal solutions within the constraints defined by the input parameters. RL involves one or more agents functioning as decision-makers. These learner agents interact with their environment, receiving feedback in the form of rewards or penalties. The primary goal of an agent is to maximize cumulative rewards through a closed-loop process. A reward is granted when the system's decision aligns with a desirable outcome, whereas penalties are applied for suboptimal actions. RL seeks to establish a mapping between states SS and actions AA, incentivizing positive behaviours. The environment in RL is typically modelled as a Markov Decision Process (MDP), making RL particularly effective for addressing problems with potentially multiple optimal solutions [21, 23-24]. Among the prevalent RL methods are Q-learning, double Q-learning, and prioritized experience replay.

   1) **Q-learning (QL):** QL is one of the most widely used RL algorithms. It is known for overestimating action values under specific conditions, though it is unclear whether this overestimation negatively impacts performance. QL operates by leveraging estimated, unrealized values to maximize action value estimations (Alwarafy et al., 2022).

2) **Double Q-learning:** This method addresses the overestimation issue inherent in QL by separating the maximization operation into two components: action selection and action evaluation [24, 25].

Review of Related Works

This review explores cutting-edge methodologies aimed at enhancing resource management, spectrum efficiency, and user satisfaction in 5G, 6G, and emerging wireless networks. Recent studies emphasize optimization models, machine learning (ML), game theory, and blockchain technologies to address challenges such as interference, scalability, and energy efficiency.

Attiah et al., (Rony et al., 2021b), proposes fairness-aware optimization models to mitigate uneven user distribution and inefficient spectrum utilization. Integrating fairness metrics with dynamic spectrum allocation, their hybrid framework improves user satisfaction and resource efficiency. Despite reducing congestion and enhancing performance, key limitations include susceptibility to interference and latency issues during reassociation. Mourad et al., (Salah et al., 2021), utilizes supervised and reinforcement learning to dynamically allocate resources in 5G networks. Their ML-based frameworks enhance QoS, lower operational costs, and preempt congestion. However, high-quality data dependencies and significant computational resource requirements remain challenges. Koutsopoulos et al., (Jorquera Valero et al., 2022), employs game theory to model antennas in Massive MIMO systems as autonomous agents optimizing transmission parameters. This decentralized strategy enhances efficiency and scalability while managing interference. Nonetheless, achieving convergence and avoiding globally suboptimal solutions require further research. Wang et al., [29], [30] proposes LSTM-based predictive handover management to ensure seamless transitions in high-mobility 5G environments. The approach minimizes latency and enhances user experience but faces obstacles such as data privacy concerns and computational intensity during training.

Park et al., (Reebadiya et al., 2021) leverages blockchain technology for secure and transparent spectrum sharing through tokenized resources and smart contracts. This framework ensures equitable distribution and reduces administrative costs. Challenges include scalability and the high energy demands of blockchain operations. Kaur et al., (Kaur et al., 2021b), reviewed ML applications in 6G networks, highlighting federated learning's potential to revolutionize wireless systems. However, the computational complexity of unsupervised learning and deep learning poses scalability challenges. Raza et al., (Kamal et al., 2021), optimize power control mechanisms to enhance energy efficiency and QoS in HetNet systems. Although their methods improve performance, the complexity of real-time interference management remains a significant hurdle. Ding et al., (Z. Wang et al., 2022), proposes a multi-layer framework addressing user mobility and energy demands. Their approach reduces latency and optimizes energy consumption but requires further real-world testing and scalability improvements. Hassan et al., (Siddiqui et al., 2022), explores ML-based network slicing for IoT, video streaming, and autonomous vehicles, demonstrating improved resource utilization. However, reliance on static conditions limits applicability in dynamic environments.

Xie et al., (C. Wang et al., 2023), introduces an RL-based model for adaptive spectrum allocation in 5G/6G networks, enhancing efficiency and throughput. Extensive training and reduced performance in congested environments remain barriers to real-world implementation. Khan et al., (Deepthi et al., 2024), integrates V2X with 5G/6G networks to support autonomous vehicles, improving real-time processing and connectivity. Challenges include ensuring low-latency communication in underserved areas and managing urban traffic density. Zhang et al., (rosas, 2022), utilizes deep learning for data offloading in MEC systems, enhancing latency and energy efficiency in IoT-based smart cities. Scalability and connectivity in large urban environments are critical issues. Sadiq et al., (Ullah et al., 2021), employs blockchain to secure IoT environments, ensuring tamper-proof data exchanges. High computational overhead and scalability concerns limit its adoption in large-scale, high-speed networks. Abbass et al., (Abbass et al., 2022) and (Al Haj Hassan et al., 2024), proposes multi-objective optimization using algorithms like the Hungarian method. Yasaka et al., (Yasaka et al., 2022), explore transmit power optimization in HetNets, demonstrating energy savings while maintaining throughput. Tashan et al., [9], and [42], optimizes handover processes using Fuzzy Logic Controllers, reducing radio link failures. However, incomplete parameter optimization and performance issues in high-speed scenarios remain. Recent studies emphasize hybrid approaches such as deep reinforcement learning (Agarwal et al., 2022b) and H-NOMA techniques (Ghafoor et al., 2022a, 2022b), for energy efficiency and QoS improvements. Emerging trends include integrating ML with blockchain (Salahdine et al., 2023; Shabbir et al., 2024), and dynamic resource allocation frameworks (Sridevi et al., 2024).

Table 1. Related Works Comparison

Ref.	5G HetNets	B5G	MOO	RRM	Cell Expansion	Throughput or Capacity	QoS	Fairness	SE	ML Application
(Tang et al., 2020)	✓			✓	✓	✓				DRL-Based
(Ryu & Kim, 2021)	✓		✓		✓	✓				PPO-DRL-Based
(Saddoud & Fourati, 2021)				✓				✓		Joint Microcell-based Relay Selection and RRM
(Gures et al., 2022)	✓	✓			✓	✓	✓	✓		Intelligent load balancing models based on ML
(Amani et al., 2023)	✓		✓	✓	✓	✓				SCA and CGP Approach
(Bartsiokas et al., 2023)	✓	✓			✓				✓	DQL-Based
(Iqbal, Ansari, Akhtar, Rafiq, et al., 2023)	✓			✓	✓	✓				Hybrid QL-Based
(Iqbal, Ansari, Akhtar, Farooq-I-Azam, et al., 2023)	✓			✓	✓	✓				QL-Based
(Sridevi et al., 2024)	✓			✓	✓	✓		✓	✓	DRASL-Based
Our Proposed Work	✓	✓		✓	✓	✓	✓	✓	✓	Proposed Q-Learning-based

Future Directions

Future work should explore transfer learning techniques to address scalability and real-time adaptability in ultra-dense Het-HetNets. Transfer learning allows the application of pre-trained models to new environments, reducing computational overhead and accelerating optimization. Leveraging domain adaptation and fine-tuning methods can address heterogeneity and mobility challenges while enhancing energy and spectral efficiency. Furthermore, the integration of ML and blockchain for decentralized RRM requires further investigation to improve scalability and reduce computational costs. These advancements are essential to meet the increasing demand for efficient and adaptive resource allocation in next-generation networks.

Conclusion

This comprehensive review of RRM optimization for 5G and beyond emphasizes innovations in ML, blockchain, and game-theoretic models. Hybrid approaches such as deep reinforcement learning and Q-learning-based frameworks have shown potential in addressing key challenges like interference, scalability, and QoS. These advancements cater to the unique requirements of IoT, autonomous vehicles, and smart city applications. However, persistent issues, including high computational complexity and data privacy, require continued research. The integration of ML with blockchain offers a promising avenue for secure and decentralized resource management. Future research should prioritize scalable and adaptive solutions that enhance energy and spectrum efficiency while ensuring real-time deployment and reliability under dynamic conditions. Addressing these challenges is crucial for the successful evolution of next-generation telecommunications infrastructures.

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