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A Review of Dynamic RRA Techniques on 5G And Beyond Mobile Networks

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Abstract— **The 5G mobile network aims to enhance wireless communication by providing faster and reliable connectivity. Open radio access network (RAN) architecture, which offers flexibility and innovation in Radio Resource Allocation (RRA), is central for optimal network performance. However, traditional RRA methods fall short of meeting the complex demands of 5G due to scalability issues. Incorporating machine learning (ML) techniques into open RAN can enhance adaptability and intelligence, ensuring that 5G networks meet high performance and service quality standards. This paper presents a comprehensive review of ML-based and traditional RRA methods in meeting the evolving demands of wireless networks. Literature from relevant articles were selected and analysed to highlight the techniques used, trends, strengths, and limitations. The findings reveal the potential and transformative impact of ML on the future of wireless communications, particularly in achieving the key performance indicators and quality of service expected from 5G and beyond networks. It also shows that research in ML-based RRA methods is at its infancy stage and more research is needed to advance the technology.**

Keywords—RRA, 5G, QoS, Machine learning, Mobile network.

I. INTRODUCTION

The pace of digital transformation is accelerating in tandem with technological advancements, necessitating faster data speeds, lower latency, and larger bandwidth in wireless networks [1]. Mobile network technologies have been rapidly evolving to meet this increasing demand, progressing from the first-generation (1G) to the current fifth-generation (5G) [1-4]. The deployment of 5G networks commenced in 2019 [4], and unlike its predecessors, 5G is distinctively designed to cater to a variety of needs through its three use cases: Ultra-Reliable and Low Latency Communications (URLLC), Enhanced Mobile Broadband (eMBB), and Massive Machine Type Communications (mMTC) [5]. The URLLC use case is specifically tailored for applications that demand real-time communication and high reliability, such as autonomous driving, industrial automation and mission-critical communications. The eMBB use case aims to provide significantly higher data speeds and greater capacity, accommodating high-definition video streaming, virtual reality, and augmented reality experiences. Moreover, the mMTC use case is designed to support multitudes of devices in densely connected networks, which is crucial for Internet of Things (IoT) applications in areas like smart cities, agriculture and energy management [5]. Fig. 1 provides a visual representation of these 5G use cases and their practical applications. The incorporation of these use cases into the 5G network infrastructure is pivotal in enhancing the quality of service (QoS) for users and equipping the network to cater to diverse requirements. This includes enabling the network to handle a broad spectrum of needs, from high-speed data transfer to reliable and real-time communication, facilitating the connectivity of a massive number of devices. This integration fosters growth and innovation across various industries and creates opportunities for digital transformation in sectors such as agriculture, healthcare, transportation, manufacturing, and entertainment.

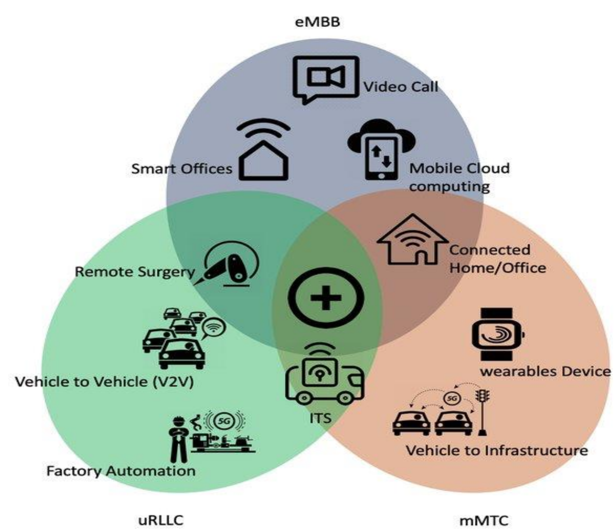

Fig. 1. 5G use cases and applications [5]

To achieve the key performance indicators (KPIs) for 5G and beyond, there is a need for flexibility, interoperability and efficient network architectures. To address these demands, the open Radio Access Network (RAN) initiative was launched in 2018, led by a consortium of telecom operators, network equipment vendors, and technology companies known as the Open RAN Alliance [6, 7]. Open RAN advocates for openness within the RAN architecture, promoting multivendor interoperability, flexibility, programmability and customization [6,7]. One of the core functional components of open RAN is the RAN Intelligent Controller (RIC) [6-8]. The RIC introduces programmability and incorporates Machine Learning (ML)/Artificial Intelligence (AI) techniques, thereby infusing intelligence into the RAN. The RIC's intelligence is enabled by its capacity to host intelligent applications such as Extended Applications (xApps) in the near Real-Time (near-RT) RIC and RAN Apps (rApps) in the non-RT RIC. The RIC plays a crucial role in Radio Resource Allocation (RRA) and network resource management, including power, radio frequency spectrum and bandwidth [6-8]. It is involved in the allocation of radio resources such as frequency, power levels, bandwidth, and throughput. Consequently, RRA is expected to be effective in maintaining load balance among cells, enhancing energy efficiency, and preserving the QoS. These measures are crucial to ensuring that mobile networks operate as expected [9, 10]. Traditional state-of-the-art RRA techniques, which include both static and dynamic RRA, have been effective in allocating resources for mobile network generations preceding 5G. However, these techniques are not scalable for many User Equipment (UE), and as mobile network technologies advance, these techniques are being reconsidered due to the high number of UE that 5G and beyond mobile networks are expected to connect [10-12]. Thus, the advancements of the RIC in the open RAN architecture have introduced flexibility in developing efficient RAN management techniques by integrating ML with the RAN, enabling intelligent ML-based techniques in RRA [7, 8].

Considering the critical context, this paper presents a comprehensive review of prior research on dynamic RRA. It includes both ML-based and non-ML-based RRA approaches to augment the RRA in 5G and beyond mobile networks. These enhancements are crucial to meet the KPIs and QoS anticipated from these networks. This study selected relevant articles from the literature and analysed them to discern the various techniques employed in each approach, their strengths and limitations, potential trends, as well as a comparison of the two approaches in advancing RRA.

The structure of this paper is organized as follows: Section 2 provides a summary of existing reviews and surveys and underscores the significance of this review. Section 3 delineates the methodology employed in the creation of this paper. Section 4 offers a detailed review of some of the existing dynamic RRA techniques. Section 5 presents a comprehensive comparison of existing RRA techniques and contrasts the ML-based and non-ML-based RRA techniques. The conclusion and directions for future work are presented in Section 6.

II. Related Works

Recent review papers on 5G and beyond networks have focused on investigating ML techniques for RRA. These reviews underscore the evolution of RRA strategies to meet the complex demands of contemporary networks, which require support for high data throughput, low latency, and massive connectivity. Specifically, reviews on the application of ML in wireless communications indicate that ML algorithms can significantly enhance network management by dynamically adapting to changing network conditions, a critical aspect of efficient resource management in 5G networks. Kamal et al. [13] presented a systematic review addressing the complex challenges of resource allocation within 5G networks, with a focus on interference management and improving QoS amidst increasing cellular service demands and limited resource availability. By categorizing and evaluating various resource allocation strategies, the study emphasizes the vital role of efficient resource distribution in mitigating network congestion and enhancing service quality. Moreover, the study offered a comprehensive analysis of the existing schemes, particularly highlighting the need for innovative solutions to support the rapid expansion of network capabilities and services in 5G technologies. In the same vein, the authors in [14] critically reviewed resource allocation techniques in Device-to-Device (D2D) communication within 5G and Beyond technologies, focusing on the role of D2D in enhancing network efficiency and reducing base station load. The study examines various resource allocation algorithms and their impact on system performance, including power, time, and spectrum allocation. It also identifies key challenges such as interference management and the need for more research on automated, learning-based resource allocation methods.

Furthermore, Xu et al. [15] presented a survey on resource allocation for 5G heterogeneous networks (HetNets), covering the challenges of resource allocation in HetNets. The authors discuss various resource allocation models, emphasizing the need for efficient algorithms to mitigate interference and enable spectrum sharing. They also classify current resource allocation algorithms and proposed structures for 6G communications that incorporate ML-based and control-based resource allocation strategies. Equally, Sharma et al. [16] comprehensively surveyed resource allocation strategies for ultra-dense networks (UDNs. They delved into various emerging technologies crucial for 5G and beyond, such as long-term evolution unlicensed, cognitive radio networks, HetNets, and millimetre wave networks, examining their impact on network capacity enhancement. The authors explore various resource allocation techniques and strategies covering different scenarios of UDNs, and optimization criteria to maximize network efficiencies.

Despite these insights, there remains a gap in the literature specifically addressing the integration of ML within the open RAN architecture for dynamic RRA. This review precisely addresses this area by focusing on dynamic RRA techniques in 5G and beyond mobile networks. This paper provides an in-depth evaluation of both ML-based and traditional RRA methods, underscoring how ML can revolutionize RRA by offering adaptable, scalable, and efficient management solutions that are essential for the complex dynamics of 5G and beyond networks. This review contributes significantly to network technology by detailing the strengths and limitations of current RRA methods and suggesting directions for future research focus. It offers valuable insights for researchers aiming to enhance the performance and reliability of future mobile networks through intelligent and dynamic resource allocation strategies.

III. Research Methodology

This section delineates the systematic approach utilized in this paper to evaluate dynamic RRA techniques in the context of 5G and beyond mobile networks. We aim to bridge the gap between traditional RRA methods and the evolving needs of modern mobile networks by harnessing the potential of ML and open RAN architecture. The process begins with understanding why RRA is pivotal in modern mobile networks, particularly within 5G. We then discuss the core use cases of 5G - eMBB, URLLC, and mMTC, provide an overview of the RIC, and define the problem statement. We further analyse existing research on both ML-based and traditional/non-ML-based RRA techniques. This aims to uncover how different approaches tackle resource allocation in 5G and beyond mobile networks. Relevant papers were analysed focusing on the methods, implementations, and results achieved. The relevance of the papers was based on the integration of ML into the RAN architecture, the innovation, and the limitations. Findings from the review were summarized and a comparison provided for ML-based approaches against non-ML-based approaches based on several key aspects such as flexibility, scalability, adaptability to real-time network changes, computational complexity, and overall efficiency. The findings summarized emphasize the crucial role of ML in revolutionizing RRA for 5G and beyond. The paper concludes by outlining the benefits and challenges of integrating ML and open RAN, as well as important directions for future research. Fig. 2 presents the workflow followed in this paper.

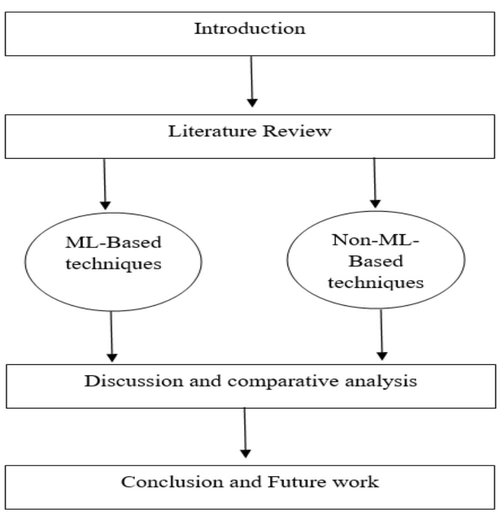

Fig. 2. Research workflow

IV. Analysis of RRA Techniques

This section presents the existing research on dynamic RRA techniques which is divided into two subsections: ML-based RRA and non-ML-based RRA. Studies for each are analysed and discussed as follows and the summary is captured in TABLE I.

A. ML-based Approaches

This technology is in its nascent stage, with only a few studies existing in this domain. These are discussed as follows: Chinchilla-Romero et al. [17] proposed a Deep Reinforcement Learning (DRL) based approach for autonomous radio resource provisioning in multiple Wireless Access Technology (WAT) private 5G RANs. This innovative solution aims to enhance network performance by dynamically allocating radio resources across different network slices, thereby ensuring compliance with Service Level Agreements (SLAs) for eMBB and URLLC services. By leveraging DRL, the study addresses the complexities of managing radio resources in environments with heterogeneous access technologies, including 5G New Radio (NR) and Wi-Fi. The proposed approach was validated via the development of a multi-WAT 5G RAN simulator, which incorporates snapshot-based approaches and analytical performance models. The simulation results demonstrated its potential to optimize resource allocation in real time, adapt to network dynamics, and improve the overall QoS. This work underscores the efficacy of DRL in navigating the challenges of next-generation network management, offering significant insights for the deployment of efficient and intelligent RANs. However, their DRL-based solution for autonomous radio resource provisioning does not directly utilize the open RAN architecture or engage with the RIC, which could introduce high computational complexity of modelling KPIs for 5G and beyond mobile networks.

Similarly, Mungari [10] proposed a Reinforcement Learning (RL) strategy for Radio Resource Management (RRM) in the open RAN architecture, leveraging an on-policy differential semi-gradient State-Action-Reward-State-Action (SARSA) algorithm for efficient RRA. The proposed RL-based RRM framework is developed as an xApp which dynamically allocates resources to meet the QoS and traffic flow KPI demands. The RL solution aims to enhance throughput across all traffic flows by handling traffic flows independently and using contextual information which includes the Signal-to-Noise Ratio (SNR) and Radio Link Control (RLC) buffer data. Moreover, the proposed framework was tested via an experiment on a 5G replicated mobile network environment, utilizing an OpenAirInterface (OAI) Software-Defined Radio (SDR) platform for the network's radio base stations (BSs) and connected with Open5GS for core network functions. The study further highlighted the need for large-scale testing in different and dynamic conditions to fully evaluate the performance of the algorithm in the open RAN architecture. However, the proposed framework primarily focuses on enhancing throughput across all traffic flows without distinctly addressing the different QoS requirements for different types of network services such as audio (voice calling), video streaming, texting, and browsing. In a similar vein, Agarwal et al. [18] proposed a Quality of Experience (QoE) enhancement function, termed QoE2F xApp, aimed at optimizing 5G open RAN-enabled HetNets for improved video service quality. The core of their solution lies in enhancing the functionality of the near-RT RIC by efficiently provisioning resources to users requesting high-resolution video services. They employ an innovative Adaptive Genetic Algorithm (AGA) for optimal user association, alongside resource and power allocation in HetNets. The proposed AGA algorithm plays a critical role in resolving the user association-resource allocation-power allocation problem. To evaluate its effectiveness, simulations were conducted utilizing an NS-3 simulator. The results demonstrated the superior performance of QoE2F xApp in terms of Video Multimethod Assessment Fusion (VMAF) and Mean Opinion

Score (MOS) for different video resolutions and user densities, highlighting its effectiveness over traditional approaches. However, their research primarily focused on optimizing the QoE for high-resolution video services, not focusing on other multimedia use cases such as audio/calls, texting, and browsing. Dynamic resource allocation in 5G and beyond mobile networks is essential, utilizing AGA as the ML algorithm compared to Deep Reinforcement Learning (DRL) algorithms might limit the QoE2F's applicability in scenarios that require real-time decision-making.

In a separate study, Munaye et al. [19] sought to address the challenge of efficiently allocating radio resources in 5G networks. They explored the application of DRL for dynamic RRA to optimize the distribution of network resources across various services, particularly for network slicing to support IoT connectivity. The study proposed a DRL-based RRA framework that utilized the network slicing concept to dynamically allocate resources for specified individual slices namely audio, texting, and video to optimize resource blocks and QoS for users. Their approach integrates round-robin scheduling with DRL optimization to enhance allocation performance and fair resource distribution. To evaluate their proposed approach, they conducted a simulation which included a period of 600 seconds, 30 user equipment units, 5 base stations, an area of 500 m^2, and a system bandwidth of 20 MHz, which allowed for up to 1000 resource slices to be allocated. The results demonstrated that the DRL approach significantly outperforms traditional single-agent Q-learning in terms of slice allocation accuracy and efficiency as the number of iterations increases. However, while advancing DRL applications in dynamic RRA for 5G networks, they primarily focus on network slicing without explicitly mentioning integration with emerging network architectures like open RAN or the utilization of RIC xApps, which could enhance scalability, flexibility, and real-time responsiveness in resource allocation. In a similar effort, Alwarafy et al. [12] tackled the challenges in RRA that arise from the introduction of heterogeneous RATs to meet the QoS demands of mobile networks as they transition towards 6G mobile networks. As ML and deep learning (DL) emerge as promising approaches to address these challenges, they demonstrated the capabilities of DRL approaches in addressing these challenges. Then, they proposed a DRL-based approach called DeepRAT to address the dynamic power allocation and multiple RATs RRA in 6G HetNets, effectively addressing the significant challenges of scalability, complexity, and the dynamic nature of next-generation mobile networks. Their approach emphasizes the importance of leveraging advanced ML techniques to manage the requirements and capabilities of future mobile networks. They conducted a simulation to validate the functionality of DeepRAT involving a multi-RAT HetNet which comprised two OFDMA-based RF subsystems, serving three single-antenna multi-mode Edge Devices (EDs) moving with random speeds and requesting QoS data rates. The objective was to maximize the sum rate via joint RATs-EDs assignment and downlink continuous power allocation, considering the QoS requirements of Eds. The DRL-based DeepRAT algorithm achieves a relative accuracy of 97.1% and 95.57% for two different RATs (RAT1 and RAT2). However, they highlighted the complexity of integrating DRL-based technologies in the network infrastructure without disrupting service. They did not explore the capability of the RIC or utilize the advantages of the xApps and rApps.

B. Non-ML-based Approaches

Studies based on dynamic RRA strategies are discussed as follows: Samorzewski et al. [20] suggested a QoS-based Resource Optimization Use Case (QBRO-UC) for open RAN, facilitated through an xApp developed for the micro-Open Network Operating System (μONOS) RIC. The objective was to enhance Radio Resource Management (RRM) within open RAN ecosystems, with a focus on optimizing physical resource block (PRB) allocations to meet diverse QoS demands. The study leverages the SD-RAN software platform, created by the Open Networking Foundation (ONF), to simulate the xApp's operational environment, providing a comprehensive overview of the communication protocols and interfaces essential for its deployment. The proposed solution employs an algorithm designed to efficiently allocate resources among various network slices, each characterized by unique QoS requirements. xApp performance was verified in the SD-RAN environment, simulating a system with two one-cell base stations and six UE units moving on a path connecting both BSs. The simulation scenario allowed for the testing of various mobile services with different 5QI values. The tests evaluated the xApp across different resource allocation strategies (EQUAL, PREFER-3, RESERVE) and under various A1 policies controlling different QoS parameters. Experimental results demonstrate the xApp's capability to dynamically manage PRB allocations, achieving significant improvements in QoS fulfilment across different network slices. However, there were challenges in coordinating multiple xApps that coexisted and ran simultaneously.

Concurrently, Rahimi et al. [21] suggested a dynamic resource allocation framework for an SDN-based virtual Fog-RAN in 5G and beyond networks. This was to minimize network power consumption and increase user satisfaction by optimizing the association of UE with Radio Units (RUs), the allocation of PRBs, and RU power allocation based on real-time traffic loads. The authors tackled this optimization challenge by formulating a Mixed-Integer Non-Linear Problem (MINLP) and a Multiple Knapsack Problem (MKP), applying Successive Convex Approximation (SCA) and a Genetic Algorithm (GA) to solve these problems, respectively. Performance evaluation was carried out via comprehensive simulations on MATLAB, simulating a single-cell scenario with 20 RUs. Key parameters such as the network size, the number of RUs and PRBs, maximum and minimum transmit power levels of RUs, and the power consumption of active and sleep states of RUs were set to reflect realistic network conditions. The findings revealed the potential of combining advanced optimization techniques with practical algorithms (SCA and GA) to efficiently manage and allocate resources effectively. Similarly, Jeon et al. [22] focused on coordinated dynamic spectrum sharing (CSS) for 5G and beyond networks, introducing a framework that enhances spectrum efficiency through dynamic sharing. The approach incorporates both centralized and decentralized spectrum-sharing mechanisms, managed by a spectrum-sharing manager. This is aimed at overcoming the limitations of static

TABLE I. SUMMARY OF EXISTING STUDIES ON RRA APPROACHES

Authors	Year	Contributions	Approach	Implementation & Evaluation	Limitations
Chinchilla-Romero et al. [17]	2023	Network Performance	DRL for autonomous RRA in 5G RANs	***Simulation/Experiment***: Yes: DRL, Python, Stable baselines3 in PyTorch, OpenAI Gym, two processors Intel(R) Core (TM) i7-9700 CPU 3.00 GHz and 32 GB of RAM. ***Evaluation***: Throughput, packet loss ratio (PLR), latency, resource utilization.	Doesn't utilize open RAN architecture or engage with RIC.
Mungari [10]	2021	Throughput Enhancement	RL with SARSA for RRN in open RAN	***Simulation/Experiment***: Yes: RL, MATLAB, OAI SDR, eNB, Open5GS EPC and ETTUS Universal Software Radio Peripheral (USRP) B210 Board. ***Evaluation***: Throughput, Signal-to-noise ratio	Focuses on throughput without addressing various QoS requirements
Agarwal et al. [18]	2022	Video Service Optimization	AGA for QoE enhancement in 5g HetNets	***Simulation/Experiment***: Yes: NS3, Evalvid framework and AGA. ***Evaluation***: VMAF, MOS.	Primarily focusing on high-res video, neglecting other multimedia uses, has limited applicability in real-time decision-making.
Alwarafy et al. [12]	2021	6G Network Scalability	DRL for dynamic power and RATs RRA in 6G HetNets	***Simulation/Experiment***: Yes: DRL, DQN and multi-agent Deep Deterministic Policy Gradient (DDPG) algorithms. ***Evaluation***: Accuracy, Spectrum efficiency, energy efficiency, Sum-rate maximization and QoS satisfaction.	Struggles with integrating DRL technologies seamlessly and lacks exploration of RIC capabilities.
Munaye et al. [19]	2021	Network Slicing	DRL for dynamic RRA to support IoT connectivity	***Simulation/Experiment***: Yes: DRL, 5G network scenario simulation. ***Evaluation***: QoS satisfaction, resource allocation efficiency.	Focuses on network slicing without integrating into open RAN or using RIC xApps, hindering scalability and responsiveness.
Samorzewski et al. [20]	2023	QoS Demands	QoS based RRM in open RAN	***Simulation/Experiment***: Yes: ONOS-based SD-RAN platform, RAN simulator. ***Evaluation***: Bandwidth allocation efficiency, service agreement compliance, adherence to A1 policies and throughput.	Faces challenges in coordinating multiple simultaneous xApps.
Rahimi et al. [21]	2021	Power Consumption	Dynamic RRA in SDN-based virtual Fog-RAN	***Simulation/Experiment***: Yes: MATLAB, SDN-based virtual Fog-RAN. ***Evaluation***: Network power consumption and efficient resource allocation.	Faces potential challenges with the complexity and scalability of optimization frameworks, including MINLP solutions and genetic algorithms
Jeon et al. [22]	2019	Spectrum Efficiency	CSS for dynamic spectrum sharing in 5G and beyond networks	***Simulation/Experiment***: Yes: MATLAB, Successive Convex Approximation (SCA), Genetic Algorithm (GA). ***Evaluation***: Spectrum efficiency, power Consumption and interference levels.	Challenges of implementing and managing dynamic spectrum-sharing in highly dense networks, particularly regarding operational complexity and multi-vendor interoperability.

spectrum allocation and improving throughput and access delay in highly dense networks. The simulation setup mirrors a realistic environment compliant with the 3GPP performance evaluation method, comparing CSS with existing technologies like Licensed Assisted Access (LAA) and Wi-Fi. The simulation models small cell clusters with varying numbers of base stations (BSs) for two mobile network operators (MNOs), employing the 3GPP urban microchannel model and considering both full-buffer and non-full-buffer traffic scenarios. A single 20 MHz channel is shared among the MNOs for CSS, LAA, and Wi-Fi scenarios, whereas each MNO has its own 10 MHz channel in the CBRS-GAA scenario. Results from the simulation demonstrate that CSS significantly outperforms LAA and Wi-Fi in terms of user-perceived throughput and access delay, especially in high-density scenarios.

V. DISCUSSION

This paper presents a comprehensive review of various works, focusing on their respective approaches, main contributions, and limitations. We focused on both ML-based and non-ML-based methods that have been proposed in previous research works to enhance RRA and management. The summary of the findings is presented in TABLE I while TABLE II compares ML and non-ML-based RRA techniques, especially in complex and dynamic network environments. As shown in Table 1, the research in RRA is in its early stages, and not much research has been done. From the year 2019 to 2023, research trends in RRA have increasingly focused on the integration with emerging technologies such as AI and ML [10, 18, 19]. These methods are being utilized to enhance the efficiency and adaptability of resource allocation in modern networks, such as in 5G and beyond. Furthermore, there has been research into how resource allocation can be optimized within advanced network architectures like SDN and network function virtualization (NFV) [21]. NFV technologies enable more dynamic and flexible management of network resources, accommodating diverse service demands and improving the QoE for users. This period has marked a shift towards more automated, intelligent, and user-centric approaches in managing radio resources to meet the demands of the increasingly dense HetNets environments.

TABLE II ML-BASED VS NON-ML-BASED RRA

Parameter	Non-ML-Based Techniques	ML-Based Techniques
Approach	Relies on predefined rules, optimization models, or algorithms without real-time adaptability.	Utilizes algorithms to dynamically allocate resources based on real-time data, patterns, and predictions.
Flexibility and Scalability	Lower flexibility, manual configuration or redesign is needed as conditions change.	Highly flexible and adaptable to various conditions and user demands due to learning capability.
Complexity	Less computationally intensive with simpler algorithms or heuristics.	High computational complexity, especially for deep learning models.
Real-time processing	Less effective in real-time adaptation, particularly in dynamic network environments (5G and beyond network).	Capable of real-time processing and adaptation depending on network complexity and chosen algorithm.
Scalability	Challenging to scale in growing and complex network environments.	Highly scalable, capable of handling large-scale networks due to learning from large datasets.
Efficiency and performance	Performance depends on the accuracy of models and may not be reliable in dynamic environments.	Potentially higher efficiency and performance due to learning complex and optimal resource allocation strategies.
Integration with modern RAN architectures	Requires significant modifications for integration, not easily accommodated in complex architectures.	ML algorithms can integrate with modern open RAN architectures via its xApps and rApps, enhancing RAN capability and intelligence.
Requirements	Relies on network experts for design and optimization, no data is needed for training.	Requires training data for algorithm learning, and expertise in ML/DL development for model creation.
Future Proof	Less future-proof, requires updates or redesigns for changing network environments.	More future-proof, ML algorithms can continuously learn and adapt to evolving network demands and technologies.

Moreover, some of the ML algorithms that have been effectively used include RL [10], DRL [19], AGA [18], and SARSA [10]. Among the key achievements based on the studies considered in the review include Chinchilla-Romero et al. [17] which improved network performance via dynamic radio resource allocation; and developed a multi-WAT 5G RAN simulator while Mungari [10] developed a xApp for dynamic RRA, improving throughput across all traffic flows. Similarly, Agarwal et al. [18] introduced QoE2F xApp for resource provisioning for high-resolution video services and Alwarafy et al. [12] demonstrated DeepRAT to address the scalability and complexity of 6G networks through DRL. In the same vein, Munaye et al. [19] suggested a DRL-based framework to optimize resource allocation and QoS while Samorzewski et al. [20] improved the PRB allocations using a µONOS-based xApp to meet diverse QoS demands. Equally, Rahimi et al. [21] minimized network power consumption and increased user satisfaction with optimized UE association and PRB allocation while Jeon et al. [22] improved efficiency and throughput, and reduced access delay through CSS managed by an SSM. Each of these studies demonstrates innovative ML applications for enhancing RRA ecosystems, showcasing the potential of ML to adapt and optimize network performance in real-time, under varying network conditions. However, our study revealed that despite the advantages ML techniques offer in RRA as highlighted in TABLE II, only a few researchers focused on enhancing RRA by integrating ML in open RAN architecture, while utilizing the RAN enhancement applications in the RIC, stressing the necessity for future work on RRA in open RAN.

VI. CONCLUSION

In this paper, we conducted an exhaustive review of dynamic RRA techniques for 5G and beyond networks, with a focus on both ML-based and non-ML-based methods. We delved into the integration of ML within the open RAN architecture and its potential to enhance RRA through intelligent algorithms such as RL, DRL, AGA, and SARSA, based on previous research works. Our analysis underscored the significance of ML in adapting to and optimizing network performance in real-time, addressing the RRA challenges of 5G and beyond network environments. However, the paper also identifies the need for further research, particularly in the integration of ML within open RAN and the exploration of the RIC's role, highlighting the critical path towards intelligent, efficient, and adaptable RRA/Management strategies in the evolution of wireless communications. In our future work, we aim to explore the utilization of ML algorithms, particularly DRL in the form of an xApp to enhance RRA, taking advantage of the intelligent controller in the open RAN architecture. It will also be intriguing to explore different ML algorithms for efficient RRA.

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