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Review

Towards 6G Technology: Insights into Resource Management for Cloud RAN Deployment

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Abstract: Rapid advancements in the development of smart terminals and infrastructure, coupled with a wide range of applications with complex requirements, are creating traffic demands that current networks may not be able to fully handle. Accordingly, the study of 6G networks deserves attention from both industry and academia. Artificial intelligence (AI) has emerged for application in the optimization and design process of new 6G networks. The developmental trend of 6G is towards effective resource management, along with the architectural improvement of the current network and hardware specifications. Cloud RAN (CRAN) is considered one of the major concepts in sixth- and fifth-generation wireless networks, being able to improve latency, capacity, and connectivity to huge numbers of devices. Besides bettering the current set-up in terms of setting the carriers' network architecture and hardware specifications, among other potential enablers, the developmental trend of 6G also means that there must be effective resource management. As a result, this study covers a thorough analysis of resource management plans in CRAN, optimization, and AI taxonomy, and how AI integration might enhance existing resource management.

Keywords: sixth generation of wireless network; cloud radio access networks; resource management; machine learning; federated learning

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1. Introduction

The Internet of Things (IoT) is the most extensively used framework in the world of information and communication technology (ICT). As of 2023, the estimated number of devices connected to IoT is around 14.7 billion [1,2], and these different applications of IoT are increasing the amount of collected data at an alarming rate [3,4]. Additionally, a significant rise has been observed in the usage of multimedia services via wireless networks [1,5]. New service classes such as ultra-high-speed, low-latency communications (uHSLLC), ubiquitous mobile ultra-broadband (uMUB), and ultra-high data density (uHDD) have been described for 6G networks. Mobile users can receive high-speed data at up to 1G bits/s over uMUB, whereas uHSLLC considers communication quality factors such latency (milliseconds) and dependability (99.999%) [6]. The number of connected devices employing IoT amounts to one million connections per km^2, as is highlighted by uHDD. Given current and upcoming developments in wireless communications, 5G may not be able to satisfy demand in the future [7]. To facilitate communication across a broad spectrum of physical, cyber, and biological universes, 6G determination will function as a distributed neurological system. This will usher in a day when everything will be recognized, connected, and intelligent. As a result, this will also provide the intelligence of everything with a solid foundation. Figure 1, shown below, provides an example of linked cognitive elements and publics [8].

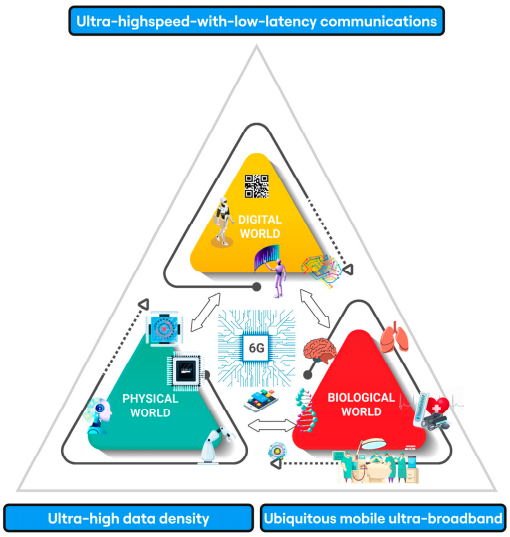


Figure 1. Services and usage scenario for 6G [8].

There seems to be a slight overestimation of what can be achieved in the next two years, but a vast underestimation of what can be accomplished in a decade [9]. Ultra-high speeds, ultra-reliable wireless, intuitive AI, and sensing technologies are going to drive a many aspects surrounding our day-to-day life in a drive towards bloom that will commence come the year 2030 and beyond. The five major categories of use cases have been defined, among which the mMTC, eMBB, and URLLC are extensions and combinations of the use cases that have been defined in 5G, while sensing and AI are two new use cases that will flourish in the era of 6G as depicted in Figure 2 [9].

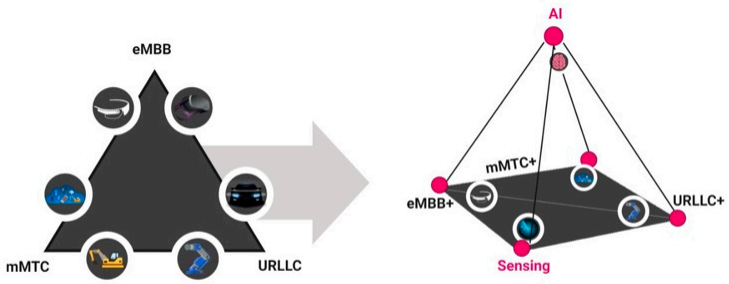


Figure 2. Connected intellect: moving from associated publics and things [9].

Achieving a high data rate, spectral efficiency (SE), and energy efficiency (EE) should be given priority in the construction of the architecture of 6G networks [10,11]. New radio (NR) 6G networks are anticipated to meet these requirements, as they are predicted to effectively manage spectrum resources to meet future data demands and support a range of devices. According to current research, NR refers to a group of radio access technologies that are intended to transmit data with minimal latency, minimal power consumption, and maximum efficiency of the available spectrum. If traditional radio access networks (RANs) do not stay competitive in the rapidly evolving mobile internet space, they risk becoming excessively costly and energy-intensive. Inefficient station use could arise from the underutilization of some base stations and overburdening of others due to the fluctuations in user traffic.

To overcome these issues, cloud RAN (CRAN) emerges as an innovative architecture [12] to address the limitations of existing RAN structures by centralizing wireless cloud network management. IBM initiated the concept of CRAN in 2010, with China Mobile later elaborating on it [13]. Centralized processing, resource sharing, real-time cloud computing, and energy-efficient architecture are the characteristics of CRAN [14]. The transition from traditional RAN to CRAN offers several advantages: reduced operational

expenses through centralized maintenance, lower power needs, enhanced energy efficiency, better network performance due to sophisticated signal processing, flexible software updates, and increased Average Revenue Per User (ARPU), among others. CRAN is also anticipated to be fundamental to 5G and future wireless networks [15]. An outline of the CRAN architecture is shown in Figure 3, consisting mainly of optical fiber transmission systems, remote radio heads (RRHs), and baseband units (BBUs). Baseband and packet processing are handled by the BBU pool, which serves as a common central processing hub for all cell sites. In the meantime, RRHs gather user-generated radio frequency signals and send them across optical fiber cables to the cloud. They also make it easier for consumers to receive data from the cloud. RRHs are connected to the BBU pool via CRAN's fronthaul, and the cloud/core network is connected to the BBU pool via the backhaul. This configuration makes it easy to add new BBUs, which improves CRAN's maintainability and scalability. Essentially, CRAN centralizes heavy computational processing while assigning the RRHs to handle simpler tasks like amplification, frequency conversion, and analog-to-digital and digital-to-analog conversion.

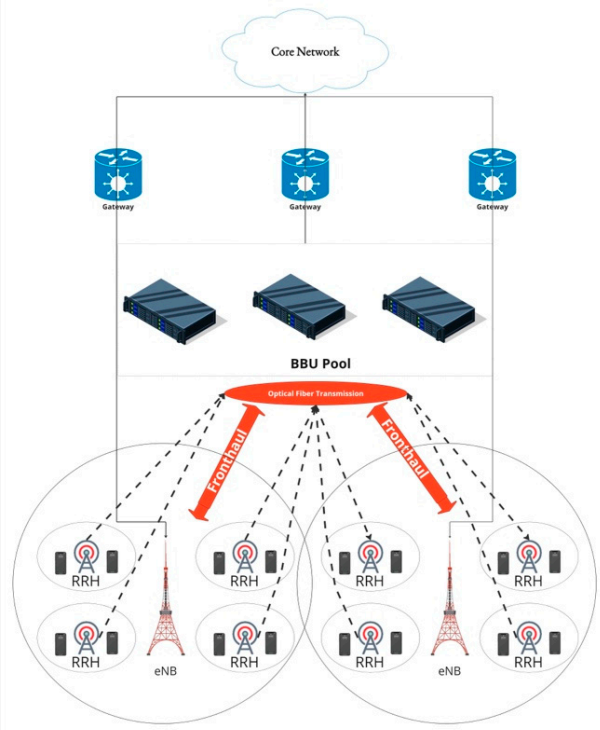


Figure 3. The architecture of cloud radio access network.

There are several advantages that the CRAN design offers to 5G and future network generations. First off, in comparison to traditional cellular networks, it enables more effective resource usage through a centralized BBU pool, resulting in 15% less CAPEX and almost 50% less OPEX [13]. Secondly, CRAN effectively supports advanced LTE features such as CoMP and interference mitigation [15]. Thirdly, it has the potential to reduce the power consumed significantly by switching off some BBUs in the pool without impacting overall network coverage, with ZTE estimating a power saving of 67–80%, depending on the number of cells a BBU covers [16]. Fourthly, it is scalable and can adapt to non-uniform traffic.

Recent studies indicate that CRAN's performance, in terms of throughput and energy efficiency, can be greatly enhanced by efficient resource allocation schemes [17]. The high dynamics of the network, the heterogeneity of the network architecture, and the complexity of network resources pose significant challenges in terms of resource orchestration. To overcome these challenges, 6G networks aim to extensively leverage new air interfaces,

innovative network architectures, and, crucially, advanced AI technologies to further enhance network performance.

2. Research Motivation and Contributions

This article introduces new research concerns, identifies and discusses potential solutions to resource management challenges, and presents a taxonomy for CRAN resource management in 6G wireless networks, all of which constitute major contributions. Many issues that arise when creating and reintroducing new study fields are covered in this survey. The contributions of this paper are as follows:

1. The current studies on the resource management element of CRAN are thoroughly examined in this article.
2. It outlines the main goals and limitations of the resource management strategies in use today and offers the most effective way to get around the current issues.
3. It offers a thorough categorization of the constraints, functions, and objectives related to the CRAN optimization problem in 6G.
4. It provides examples of comparable articles that integrated CRAN and artificial intelligence in resource management and explains how new technologies such as federated learning can improve the management process.

This article's remaining sections are as follows: A literature survey of resource management research is provided in Section 3. A taxonomy that demonstrates resource management in 6G using a cloud radio access network is shown in Section 4. We describe the integration of machine learning into resource management in Section 5. Several publications on resource management, using cloud radio access networks and artificial learning, are highlighted in Section 6. Section 7 presents the conclusion. Figure 4 depicts the study's organizational structure.

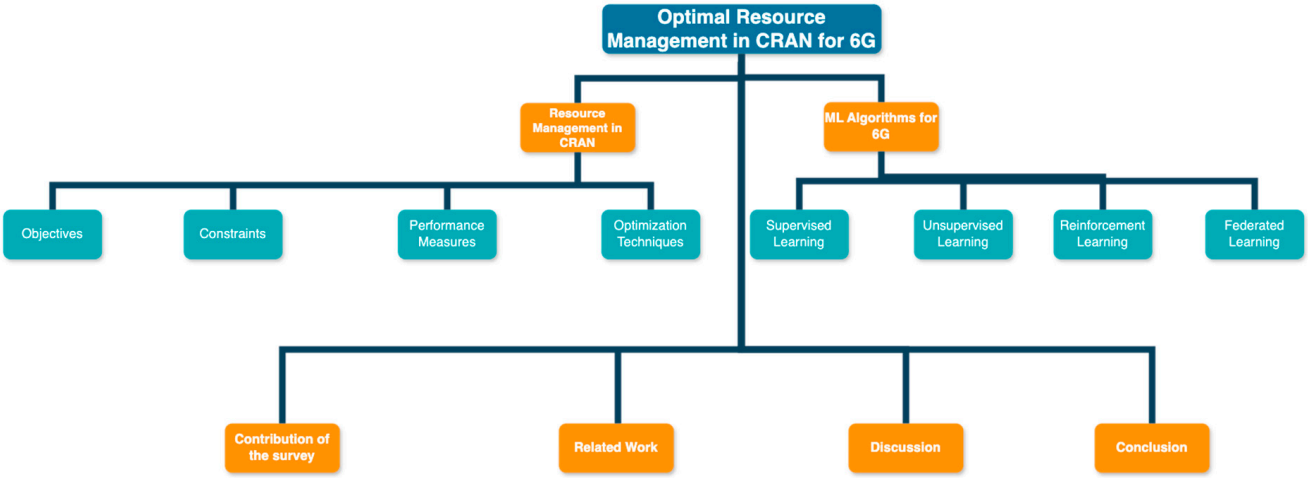


Figure 4. The organization of this survey work.

3. Related Works

This section provides a concise review of related papers and discusses surveys on the CRAN structure to compare them with our work. The authors in [18] offer a thorough survey of 6G cellular networks, considering a broad spectrum of 6G features and introducing key performance indicators (KPIs) and new use cases. They explore various potential technologies that will significantly contribute to 6G and underscore the potential requirements, challenges, and trends in 6G. A thorough analysis of 6G heterogeneous networks' (HetNets') resource management is provided in [19]. The goal of this study is to give crucial background information on HetNets so that more efficient techniques can be developed in this field.

An overview of resource allocation systems is provided by the research in [8], which also gives a thorough understanding of the goals, limitations, problem categories, and approaches to solving in CRAN. In addition, it addresses application-specific objectives and the development of use cases for CRAN, as well as the difficulties and unresolved problems in CRAN in relation to 5G and other networks. Notable research efforts have been devoted to exploring and developing logical strategies for allocating resources with the goal of providing excellent quality of service (QoS) to an ever-growing user base. The distribution of resources in several ultra-dense network scenarios is covered in [20]. Combining the optimization of radio resource allocation with other methods is the main subject of the survey of newly investigated HetNet radio resource management techniques presented in [21]. These schemes are grouped for a qualitative examination and comparison using their optimization metrics. A computational and implementation complexity study of the RRM schemes is also presented in this paper.

One article [22] presented a comprehensive survey on resource allocation (RA) in HetNets for 5G communication. It presented two possible architectures of 6G communication for organizing RA issues in next-generation HetNets as a learning-based RA architecture and control-based RA architecture. To achieve resource allocation and efficient load balancing, the authors of [23] suggested the Hybrid Quantum Deep Learning (HQDL) model, which combines convolution neural network (CNN) and recurrent neural network (RNN). By suggesting an intelligent radio resource management method in order to tackle traffic congestion and by demonstrating its effectiveness on a real-world dataset obtained from a big operator, [24] exemplifies the role of intelligence in O-RAN. One paper [25] thoroughly reviews and assesses the categorization of emerging resource distribution strategies in 5G by sorting these methods in order to improve service quality. It includes a conversation revolving around the benchmarks used for performance assessment. Meanwhile, [26] introduces remote radio head group-based mapping (RGBM), designed to lower energy use at the baseband unit (BBU) pool, considering the quality of service (QoS) for users and the limitations of BBU capacity.

The research in [27] presents a thorough review of the cutting-edge resource management strategies recently introduced for cloud radio access networks (CRANs). It organizes these strategies into two groups: radio resource management (RRM) and computational resource management (CRM), with further subdivisions and examinations based on the approaches adopted in various studies. Artificial intelligence (AI) plays an integral role in developing and improving protocols, architecture, and processes for 6G networks [28,29]. Machine learning techniques are employed to fine-tune applications within 6G networks [30], while explainable AI is enhancing trust between humans and systems, thereby bolstering the dependability of forthcoming 6G communication networks [31]. AI and machine learning algorithms are being used to elevate quality-of-service (QoS) metrics for 5G and 6G networks. A hybrid machine learning model achieved an impressive 95.17% accuracy rate in beyond-5G (B5G) communication networks [32]. AI-driven architectures provide solutions for 6G challenges, including hardware development, energy management, computational efficiency, and the robustness of algorithms [33]. The discrepancies between our study and the current surveys are compiled in Table 1 to demonstrate our contributions. In this, the research question of the survey is the topic discussed.

Table 1. Current surveys on relevant subjects.

Year	Ref.	Focus of Survey	Resource Management	CRAN	Integration of AI
2021	[18]	This study examines the demand for 6G networks, prospective 6G demands and patterns, current research initiatives, and novel services.	×	×	√
2021	[8]	Based on performance criteria, this article discusses and assesses the current evolving resource allocation systems in 5G.	√	×	×

Table 1. *Cont.*

Year	Ref.	Focus of Survey	Resource Management	CRAN	Integration of AI
2023	[19]	The goal of the study is to provide a thorough survey of HetNets and the most recent research on resource management topics.	√	×	×
2022	[34]	An overview of the intelligent load balancing models for generic problem-based of HetNets.	×	×	√
2021	[21]	This investigation examined optimization criteria, methodologies, and methods for resource allocation problems, as well as the challenges in ultra-dense networks (UDNs).	√	×	×
2020	[22]	The combined optimization of radio resources was the main emphasis of this survey's study of HetNet radio resource management (RRM) systems for heterogeneous networks.	√	×	×
2021	[23]	It offers a thorough analysis of HetNet resource allocation for 5G communications. It presents many HetNet scenarios.	√	×	×
2020	[20]	Together with an extensive optimization taxonomy covering several facets of resource allocation, this paper offers a thorough analysis of resource allocation techniques in a CRAN.	√	√	×
2022	[35]	A thorough overview of machine learning-based RRM algorithms for 5G and beyond-5G networks is given by this paper.	√	×	√
2023	[36]	An overview of the function of AI/ML algorithms and their use for resource management in edge computing are given in this survey.	√	×	√
2024	This work	This survey provides a detailed taxonomy about resource management in the future 6G cloud area networks in terms of its objectives, constraints, and performance analysis. Also, we describe how machine learning/deep learning algorithms can improve their performances.	√	√	√

4. Resource Management in CRAN

Allocating resources is a crucial element of wireless network systems, especially within the context of 5G and forthcoming 6G networks. The latter networks must be adept and agile in meeting a variety of network demands. These encompass managing power, distributing bandwidth, strategizing deployment, and coordinating resource association [37]. For any mobile network framework, the role of resource distribution is pivotal in maintaining seamless access for users, corporate entities, and clients who utilize cellular network services. A key obstacle for 6G technology is the efficient distribution of resources, which is essential for ensuring the endurance of battery-powered devices and the quality of service for applications. Users are calling for resource allocation and management techniques that are both effective and efficient. The rigid services and inflexible infrastructure of existing networks contribute to a resource allocation process that is both complicated and suboptimal [38]. Figure 5 shows a generalized taxonomy for resource management in 6G.

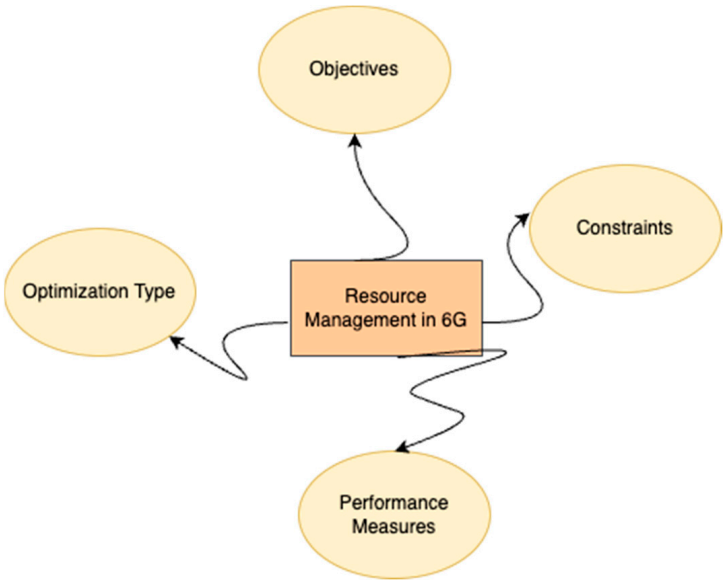


Figure 5. Taxonomy of resource management in 6G.

4.1. Objectives

Resource management in cloud radio access network architecture within the context of 6G wireless networks is a complex and crucial aspect of their operation. The objectives in this context are to optimize the performance, efficiency, and capabilities of the network infrastructure. Here are the key objectives:

1. Efficient spectrum utilization: One of the primary objectives of resource management in cloud RAN for 6G is to efficiently utilize the available spectrum. This includes managing interference and ensuring that frequency resources are allocated optimally to meet user demands and network conditions.
2. Energy efficiency: Cloud RAN must be designed to minimize energy consumption, which is a significant concern in 6G networks. This involves optimizing the operation of network elements (like base stations) and leveraging energy-saving technologies, contributing to more sustainable network operations.
3. Quality of service (QoS) and experience (QoE): Ensuring a high QoS and QoE for users is a key objective. This involves managing resources to provide high data rates, low latency, and reliable connections for applications requiring this.
4. Dynamic and scalable resource allocation: Cloud RAN in 6G should be capable of dynamically allocating resources based on real-time demands and network conditions. Scalability is also vital to adjusting resources as the number of users or the nature of applications evolves.
5. Enhanced security and privacy: With the increasing complexity and openness of 6G networks, ensuring robust security and privacy becomes more challenging and essential. Resource management strategies must include measures to protect against threats and ensure data privacy.
6. Cost-effective operations: Efforts to achieve the efficient management of resources in cloud RAN should also aim to reduce operational and capital expenses. This includes optimizing network deployment and maintenance costs.

These objectives highlight the need for developing advanced, intelligent, and efficient resource management strategies in cloud RAN to fully leverage the capabilities of 6G technologies and meet the evolving demands of users and applications. Therefore, we classify objectives in CRAN into seven basic categories, as shown in Figure 6 [20].



Figure 6. Taxonomy of objectives for resource management in 6G.

4.1.1. Resources

Some research focuses on how resources are distributed, aiming to achieve specific objectives such as assigning users, maximizing the network's total user capacity, and choosing which remote radio heads (RRHs) to use for planning. The method proposed in [39] seeks to coordinate the scheduling of user assignments across both resource blocks (RBs) and RRHs to satisfy the significant demands for backhaul link capacity found in centralized RANs (CRANs). The issue of increasing user capacity in H-CRANs is addressed in [40] by implementing an outer approximation algorithm. To improve spectral efficiency in cloud-based cognitive RANs, techniques have been developed to enhance the number of users per channel, as mentioned in [41]. Furthermore, algorithms for balancing resources have been utilized to solve problems related to channel and power distribution. According to [42], a combination of pilot allocation and beamforming design has been explored to increase user acceptance in densely populated time-division duplexing (TDD)-centralized RANs.

According to the study in [43], each base station (BS) is assumed to continuously send data to its connected user equipment (UE) based on the signal-to-noise ratio (SINR). This deep learning approach is specifically designed for ultra-dense networks, smartly matching user devices to the most appropriate macro base stations (MBS) and small-base stations (SBS).

The research in [44] delved into the complexities of user association in heterogeneous networks (HetNets) with millimeter-wave technology, which involves a variety of radio access technologies. Finally, the research presented in [45] tackled a combined challenge of UA and resource distribution. The authors aimed to improve energy efficiency in clusters

within beyond-5G (B5G) heterogeneous networks (HetNets), with the goal of boosting the overall system energy efficiency (EE) and minimizing interference.

4.1.2. Energy

In addition, energy consumption is one of the key objectives for CRAN. In the study referenced as [46], the authors investigated how to minimize the overall transmission power in a centralized radio access network (CRAN) by utilizing a stochastic coordinated beamforming approach. Additionally, other research [47] focused on reducing the power usage of the BBU pool through a novel BBU virtualization strategy. With this method, BBU computing resources can be shared dynamically across all cells under the guidance of a heuristically simulated annealing algorithm. Techniques for reducing the overall transmission power while abiding by the constraints imposed by backhaul capacity were investigated in article [48].

In study [49], Lee et al. explored the balance of power use between base band units (BBUs) and remote radio heads (RRHs), developing a theoretical model to aggregate BBUs. This model was aimed at identifying the ideal traffic load threshold that would trigger RRHs to switch, thereby reducing the network's overall power consumption. The study in [50] addressed the optimization of energy efficiency across downlink transmissions in a dual-layer heterogeneous network, incorporating multiple small cells.

4.1.3. Throughput

The sum-rate, a crucial measure of network efficiency that accounts for unequal source rates [51], is optimized within the operational constraints of cloud radio access networks through comprehensive search strategies in coordinated scheduling tasks. The research detailed in [52] introduces a clustering approach for remote radio heads (RRH) that aims to enhance the total throughput of CRANs, while also reducing the energy costs associated with inter-cell collaborative processing by applying the Pascoletti and Serafini scalarization method [53]. In study [54], the uplink ergodic sum-rate in heterogeneous CRANs (H-CRAN) is increased by fine-tuning the bandwidth distribution and fronthaul compression using the radio access links. Paper [55] presents a distributed compression method designed to amplify the CRAN system's achievable rate.

Salhab et al. conducted a study on RRH clustering that was sensitive to throughput [56], with the aim of maximizing user throughput while juggling multiple BBU resource constraints. In [57], a dynamic optimization framework is put forward to minimize the total power consumption in heterogeneous networks, thereby enhancing the network's capacity and scope of coverage. Finally, in study [58], researchers examined a power optimization approach designed to manage interference within 5G networks.

4.1.4. Quality of Service

In [59], the focus was on addressing the load-balancing issue within CRAN. The primary goal was to enhance QoS and diminish the rate of call blockages. In the study conducted by Yao et al. [60], a problem was defined that considered QoS while jointly mapping baseband units (BBUs) to remote radio heads (RRHs) and associating users within a CRAN framework. To accomplish load balancing successfully, the additional research described in [61] used the self-optimized architecture for CRAN (SOCRAN) to perform semi-static cell differentiation and integration (CDI) combined with dynamic BBU–RRH mapping. Finally, based on the estimation of network load, the authors of [62] created a self-optimizing algorithm that carries out dynamic RRH clustering for cloud RAN networks.

4.1.5. Security and Privacy

In the context of 6G development, there is a pressing need to re-evaluate traditional security methodologies. Advanced techniques for authentication, encryption, access management, secure communication, and the detection of malevolent activities must meet the more stringent demands of future network architectures [63]. Furthermore, innovative

security solutions are imperative to maintaining trust and privacy. The security concerns associated with 6G technologies persist: for instance, the most critical security threats in SDN are related to potential weaknesses in the SDN controllers, communication interfaces, and application platforms. Similarly, MEC faces threats from physical attacks, Distributed Denial of Service (DDoS), and the highly distributed nature of 6G architectures [64].

The security of network slicing in 6G technology is also at risk, with potential threats such as information theft and Denial of Service (DoS) attacks. Furthermore, compromising network automation technologies can significantly hinder the 6G network's ability to maintain its dynamic nature and extensive automation capabilities [65].

A layered security architecture might be useful in 6G networks for differentiating communication security at the sub-network level from wider area network security protocols. This entails the coordination of distributed core functionality, such as User Plane Micro Services (UPMS) and Control Plane Micro Services (CPMS), with the integration of radio access networks (RANs) and core functions, centralizing upper-layer RAN services [66].

4.1.6. Cost-Effective

While cloud radio access network architectures bring numerous advantages, crafting an economical resource management system presents the primary obstacle for mobile network operators (MNOs) implementing 6G and subsequent CRAN infrastructures. Consequently, the quest for cost-effective resource management in CRAN has become a focal point of academic investigation. Musumeci and others [67] scrutinized a BBU location issue within a CRAN tied to a Wavelength Division Multiplexing (WDM) optical network, framing the optimization challenge as an integer linear programming (ILP) problem aimed at reducing the overall network expenses, represented by the active BBU sites or the optical fibers utilized for traffic flow.

Chen et al. [68] introduced an economical distributed radio access network (DRAN) layout for the deployment of 5G small cells. Meysam et al. [69] offered an ILP and a genetic algorithm designed to lower the Total Cost of Ownership (TCO) of CRAN for 5G small-cell networks and to evaluate the costs associated with transitioning to a CRAN-based Time and Wavelength Division Multiplexed Passive Optical Network (TWDM-PON) structure. Lastly, Yeganeh et al. [70] analyzed the CAPEX and OPEX involved in CRANs and mathematically formulated the problem of assigning cells to BBU pools, considering the costs related to the fronthaul network.

4.2. Constraints

Quality, power, throughput, resource, and miscellaneous are the five major categories into which Figure 7 groups the CRAN-related restrictions found in the literature.

4.2.1. Quality

In CRAN environments, the close positioning of densely distributed remote radio heads (RRHs) can lead to significant mutual interference, potentially impairing network performance and quality of service (QoS). To ensure service quality, the user's signal-to-interference-plus-noise ratio (SINR) is often factored in as a constraint during the design of cooperative transmissions in CRAN, as explored in [71]. Study [72] enhanced the energy efficiency of CRAN by implementing access control and beamforming techniques, taking into account downlink SINR constraints.

In the context of hybrid CRAN (H-CRAN), the research detailed in [73] involved assigning dedicated resource blocks (RBs) to user equipment (UE) based on its rate-constrained QoS requirements. Furthermore, this study introduced a joint strategy for optimizing both resources and power allocations within H-CRAN, with special consideration to limiting inter-tier interference.

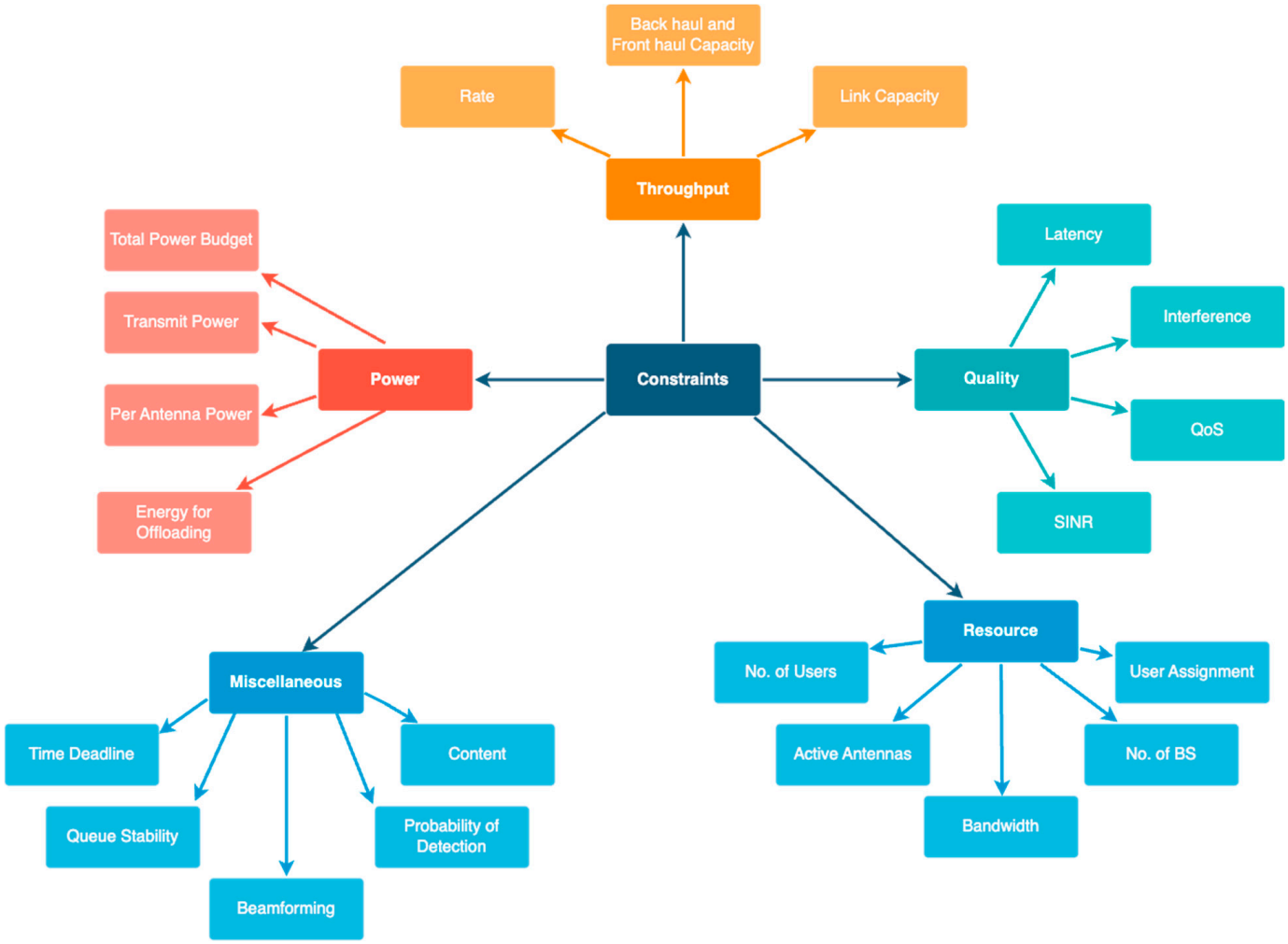


Figure 7. The classification of constraints of resource management in 6G.

4.2.2. Power

The research described in [74] delved into the optimal distribution of computational and communicational resources within a set power budget. One study [75] focused on sum power constraints, investigating their impact on sum-rate maximization and selecting the best antennas during the downlink operations for distributed MIMO cloud RAN.

Research [76] into a massive MIMO cloud RAN enhanced the downlink weighted sum-rate by taking into account individual RRH power constraints. While many studies typically focus on sum power constraints, it is often more realistic to consider individual base station (BS) transmission power constraints.

Furthermore, in [77], the energy efficiency of energy-harvesting H-CRANs was assessed in relation to the maximum power limitations of macro base stations (MBS) and RRHs. Lastly, [78] suggested an energy-efficient method with individual base station power transmission constraints for CRAN-based NOMA.

4.2.3. Throughput

The focus on minimum rate constraints is key to enhancing cloud network throughput, especially in CRAN systems utilizing relay cooperation, as detailed in [79]. In [80], the emphasis is on meeting minimum data rate requirements per user to boost H-CRAN's energy efficiency, underlining the critical balance between user demands and energy consumption.

The role of fronthaul capacity and cloud processing limitations is pivotal in examining cooperative transmissions in CRANs to minimize network-wide transmission power, as

discussed in [71]. The issue of sum backhaul constraints is addressed in [81], aiming to enhance the overall sum-rate in uplink processing across multiple cells.

Resource allocation challenges in H-CRAN, particularly under the constraints of fronthaul capacity, are described in [80] in order to improve energy efficiency. The limitation of fronthaul link capacities between remote radio heads (RRHs) and the baseband unit (BBU) pool is considered in [82] to maximize network operator profits in H-CRAN settings.

4.2.4. Resource

The research outlined in [83] focused on limitations in terms of the number of users that can be served simultaneously, aiming to optimize the total data rate within a massive MIMO-enabled CRAN. The investigation noted in [84] described the limitations on user equipment sets connected to remote radio heads in efforts to bolster the overall throughput of CRAN systems.

Furthermore, [85] explored the allocation of resources in an energy-conscious manner within a H-CRAN, imposing a limitation that each user may only be linked to a single access point, with each access point's subcarrier being exclusively dedicated to one user. The segmentation of baseband processing tasks among multiple baseband units, as a measure to economize power consumption in CRAN through a virtualization scheme, was the central theme in [47]. This partitioning considered the needs of each base station for specific tasks. Lastly, the research in [86] highlighted the necessity of resource connectivity constraints to achieving substantial multiplexing gains, aiming to amplify the utility function across a network comprising multiple CRANs.

4.2.5. Miscellaneous

The research delineated in [87] delved into the achievable data rates in scenarios where multiple relay channels are deployed for coordinated multi-point (CoMP) operations within a CRAN, with a specific focus on the noise implications caused by Wyner–Ziv compression at the relay nodes.

In [88], the investigation centered on a beamforming vector formulation that adapts according to the state of the data queue and the Channel State Information (CSI), exploring its application in cooperative beamforming strategies for handling delay-sensitive traffic within a CRAN that has a limited backhaul capacity. The research presented in [89] took into account queue stability and the size of the data backlog when determining the compression rates suitable for uplink data transmission in a CRAN. This study proposed a network model in which the compression rate is permitted to surpass the backhaul's instantaneous capacity provided that the queue remains stable, opening avenues for more flexible data management within CRANs.

4.3. Performance Measures

In the context of 6G (sixth-generation) wireless networks, several performance measures are crucial for effective resource management. These measures typically focus on optimizing the use of available resources like spectrum, energy, and infrastructure to provide better services. Figure 8 shows the key performance measures as follows [8]:

1. Spectrum efficiency: This is measured in bits per second per hertz (bps/Hz) and is crucial in 6G due to the expected increase in data rates and the use of higher-frequency bands like terahertz (THz).
2. Energy efficiency: This is measured as the amount of data transmitted per unit of energy consumed (bits/joule). This involves optimizing network elements consuming less power and leveraging energy-saving technologies. Energy efficiency and spectrum efficiency are increasingly important in 6G.
3. Latency: The amount of time it takes for a data packet to reach the final destination is latency. Ultra-low latency is crucial for 6G applications, particularly for those involving real-time gaming, autonomous driving, and remote surgery. Usually, latency is expressed in milliseconds (ms).

4. Throughput: The speed at which information is sent across the network without error is expressed in bits per second (bps). It is necessary to manage the anticipated rise in data traffic in 6G networks.
5. Reliability: The fourth goal of 6G is extraordinarily high reliability, particularly for vital applications. The likelihood of effective data transmission within a given time frame and under defined conditions is a common way of quantifying reliability.
6. Connection density: This measures the network's ability to support a large number of connected devices per unit area.
7. Quality of service (QoS) and quality of experience (QoE): These are user-centric measures that assess how well the network meets the user's requirements (QoS) and the overall user experience (QoE).
8. Security and privacy: With the increased complexity and use cases in 6G, ensuring robust security and privacy measures is a key performance indicator.

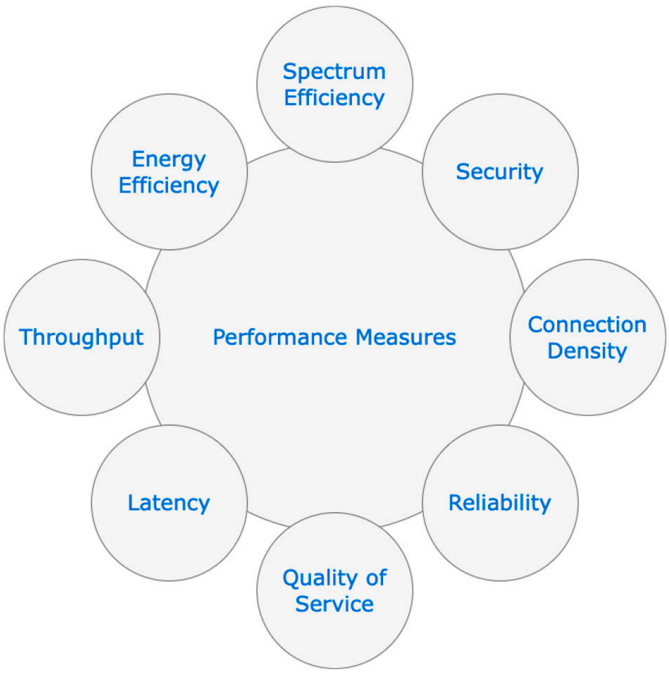


Figure 8. The key performance measures of resource management in 6G.

Each of these measures is interrelated and often involves trade-offs. For instance, improving throughput might affect energy efficiency, and ultra-low latency requirements might impact reliability. Advanced technologies like AI and machine learning, network slicing, and advanced antenna technologies are expected to play a significant role in optimizing these performance measures in 6G networks [21].

4.4. Optimization Techniques

Although resource management approaches result in high computational complexity and considerable signaling overhead, it is necessary to optimize this management to enhance performance. Therefore, in this section, several workable ways to overcome limitations of resource management are discussed.

4.4.1. Convex Optimization

Convex optimization stands out as a highly efficient strategy because it ensures the optimality of the results obtained. This approach involves minimizing or maximizing a convex objective function within a convex feasible set. One practical use of convex optimization in wireless cellular networks involves addressing resource allocation issues to optimize the use of available network resources. Optimization challenges can vary

widely, including convex/non-convex, continuous/discrete, or linear/non-linear problems that aimed to address various goals. Examples include reducing energy consumption, enhancing fairness, maximizing coverage, minimizing interference, achieving minimum data rates, maximizing overall system capacity, and optimizing the weighted sum-rate. Generally speaking, the formulation of an optimization problem can be mathematically depicted as follows [90]:

$$\begin{gathered} Minimize\ g\ (x) \\ subject\ to\text{: } gj(x) \leq bj, j = 1 \ldots n \end{gathered}$$

while the following are the problem's constituent parts:

- $x = (x_1, \ldots, x_m)$: optimization variables
- g: $R_m \rightarrow R$: objective function
- g_j: $R_m \rightarrow R$, $i = 1, \ldots, n$: constraint functions
- and the optimal solution x^*.

Convex problems have a wide range of optimal solution techniques, including traditional linear, non-linear, quadratic, mixed integer, and semi-definite programming techniques. These include the Lagrange duality method, duality theory, and descent methods, among others. For example, the topic of resource allocation at relay stations has been formulated as a convex optimization problem of minimizing power consumption at the relay station.

On the other hand, in order to discover appropriate solutions for non-convex optimization problems, it is frequently necessary to turn them into convex forms or apply heuristic techniques like greedy algorithms and sequential convex approximation (SCA). Furthermore, non-convex nonlinear programming can be used to approach problems involving both power allocation and backhaul bandwidth, which are then divided into two convex sub-problems for resolution.

4.4.2. Stochastic Geometry Methods

The stochastic geometry model is a complex mathematical tool designed for the analysis of wireless networks. The use of this technology has experienced notable expansion in domains such as sensor networks, mobile ad hoc networks, vehicular ad hoc networks, heterogeneous cellular networks, LTE-U, and cognitive radio networks (CRNs), among other ultra-dense cellular networks. The main goal of using the stochastic geometry technique is to explain why user locations or network topologies are uncertain [91]. This is because users in wireless cellular networks are unpredictable and variable. This method offers an alternative to relying on simulation techniques or deterministic models. Essentially, the analysis and optimization of network performance and QoS are grounded in the signal-to-noise ratio (SINR), which provides a mathematical foundation for assessing the network's coverage and connectivity.

4.4.3. Combinatorial Optimization

Combinatorial optimization problems require the application of mathematical techniques to select the optimal solution from a small pool of feasible solutions. These issues are crucial to solving discrete optimization problems and have close connections to both computational complexity theory and algorithm theory. An updated binary artificial bee colony method was used to develop a novel solution to a combinatorial optimization issue, aiming to maximize spectrum consumption for cognitive radio networks (CRNs). With this approach, the spectrum allocation variables are encoded as binary strings, and the pool of solutions is chosen using various selection pressure techniques [92].

4.4.4. Sparse Optimization

With the advent of ultra-dense small-cell networks, complexity and management challenges have significantly increased, making the pursuit of simple and approximate solutions

more practical than aiming for complex, exact ones. To address this, data can be represented as a collection of sparse or nearly-sparse coefficients, facilitating the derivation of straightforward optimal solutions. Sparse optimization is particularly beneficial in cellular wireless networks for its role in signal compression, reducing power consumption, and decreasing computational complexity, which are critical considerations in the energy-intensive environment of ultra-dense CRANs. To this end, the greedy sparse beamforming (GSBF) framework has been developed [93], utilizing a greedy selection algorithm to achieve an optimal solution initially. To further cut down on computational complexity, a sparse beamforming algorithm aimed at minimizing the weighted l1/l2 norm has been introduced. This framework includes two GSBF algorithms with varying degrees of complexity: a bi-section GSBF method and an iterative GSBF algorithm. Similarly, smoothed-norm approximation has been used to address the problem of sparse multicast beamforming (SBF) in order to reduce power consumption and backhaul costs. This SBF challenge is transformed into a difference of convex programs issue, which is then resolved via convex–concave procedure algorithms [94]. The optimum path planning algorithm, which is an enhanced COOT (ICOOT) optimization algorithm, is proposed by the authors in [95] in order to achieve a mobile robot capable of operating autonomously in an uncharted area containing erratic static and dynamic obstacles, as well as static and dynamic goals.

4.4.5. Machine Learning

In wireless communication systems and networking, machine learning is a useful technology that is being hailed as a viable solution for streamlining traffic unloading and improving resource allocation. In particular, the machine learning approach of reinforcement learning is notable for its capacity to function without a pre-established model or causal knowledge. Rather, it acquires knowledge by direct interactions with its surroundings, formulating tactics derived from this hands-on education. The following sections explore the different reinforcement learning approaches used in resource management and demonstrate how well they function in terms of optimizing network performance in response to changing environmental conditions. One of the many applications of machine learning algorithms is in electric power consumption. One study [96] presented a validation strategy that used artificial intelligence (AI) technology to teach electrical users how to use energy effectively.

4.4.6. Graph Theory

Graph theory is a mathematical framework that is extensively utilized for the modeling of interactions between pairs of objects, offering a method with which to solve computationally complex problems through the design and analysis of graph models. Hence, graph theory finds widespread application in various ultra-dense network (UDN) scenarios. A graph is generally represented as G = (VE, ED), where VE stands for vertices and ED denotes edges, with these elements varying according to the specific problem at hand. In most cases, the vertices represent entities within the network, while the edges signify some form of “relationship” between every pair of vertices. Graph algorithms have proven to be effective tools for resource allocation in UDNs [97].

4.4.7. Clustering

The clustering technique is acknowledged as a successful approach to problems involving high computing complexity and those requiring unsupervised learning. When small-base stations (SBSs) are closely clustered together, the overhead resulting from information sharing between them is greatly increased, which causes a spike in signaling overhead. By grouping objects into clusters based on shared characteristics, computational complexity can be markedly reduced. This approach is particularly beneficial in small-cell networks, where the resource allocation optimization problem is tackled in two distinct phases. Initially, SBSs are organized into clusters according to specific criteria. Following this, the overarching optimization problem is segmented into several comprehensive sub-

problems. Subsequently, in the second phase, a tailored resource assignment scheme is implemented for each cluster independently. This clustering process, including its types, features, and techniques, is illustrated in Figure 9.

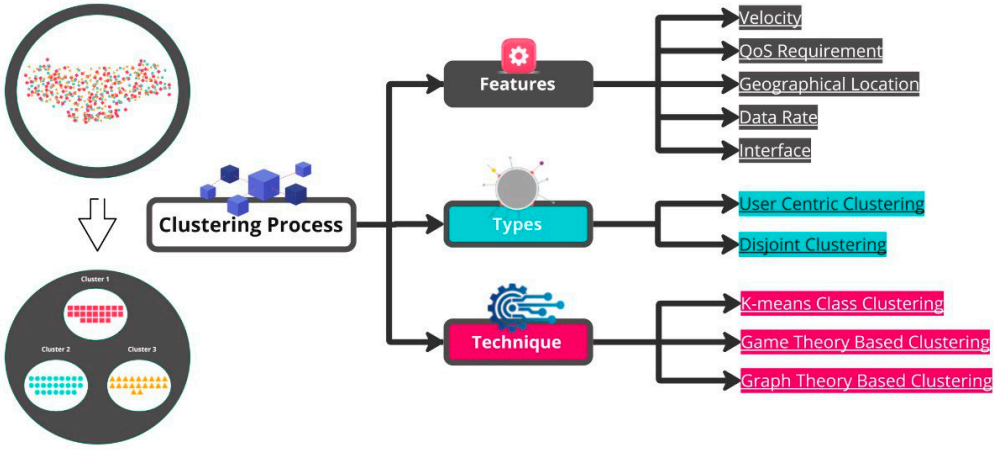


Figure 9. The clustering process.

There are two different ways to cluster base stations (BSs): disjoint clustering and user-centric clustering. The network is organized into non-overlapping clusters using the disjoint clustering approach, as used in [98], and the BSs within each cluster work together to serve all users that are within their coverage area. This method is particularly effective at minimizing interference across the network. However, it has been observed that users located at the edges of these clusters tend to experience poorer performance [99]. On the other hand, the user-centric clustering approach eliminates the concept of a fixed cluster edge. In this model, clusters can overlap as they are tailored to individual users, meaning that each user is covered by a uniquely selected subset of neighboring BSs, allowing for more personalized and potentially more efficient service coverage.

4.4.8. Auction Theory

An auction is a method of allocating resources and determining prices through bids placed by participants. In wireless cellular networks, several auction algorithms are commonly employed. These include the Vickrey–Clarke–Groves (VCG) auction [100], which is a sealed-bid auction designed to auction multiple items simultaneously to maximize social welfare; Vickrey's auction [101], another sealed-bid auction where the winning bidder pays the second-highest bid price; and combinatorial auctions [102], where multiple items are auctioned at the same time, allowing bidders to place bids on combinations of items. An auction-based distribution strategy was presented [103] to address power allocation issues in CRANs, demonstrating the adaptability and efficiency of auction methods in optimizing network resource distribution.

4.4.9. Game Theory

Game theory is an influential mathematical framework employed to address resource allocation challenges within ultra-dense networks (UDNs). This framework models scenarios involving a set of players (decision-makers) who take actions (recommendations) aimed at improving a performance measure function, such as throughput, energy efficiency, latency, spectrum efficiency or network capacity. Specifically, this is used to address sudden cell outages and facilitate self-healing in small-cell networks. This approach not only enhances the total payoff but also ensures that the payoffs for individual players are not diminished. As a result, in [104], a resource allocation algorithm based on the coalition game was presented. This method improves network performance, especially with regard to user fairness and network capacity, and efficiently handles network failures.

4.4.10. Stochastic Optimization

Stochastic optimization is a robust mathematical approach applied to address resource allocation issues across various ultra-dense network (UDN) settings. This technique employs random variables to optimize (minimize or maximize) an objective function under the conditions of uncertainty inherent to the optimization process. Such uncertainties in resource allocation may arise from random noise, interference, or channel fading. By leveraging stochastic optimization methods, problems characterized by uncertainty are tackled through formulations that incorporate random variables, leading to optimization models with random objective functions or constraints [105,106]. This allows for more flexible and accurate solutions that can adapt to the unpredictable nature of wireless network environments.

5. Machine Learning Algorithms in 6G

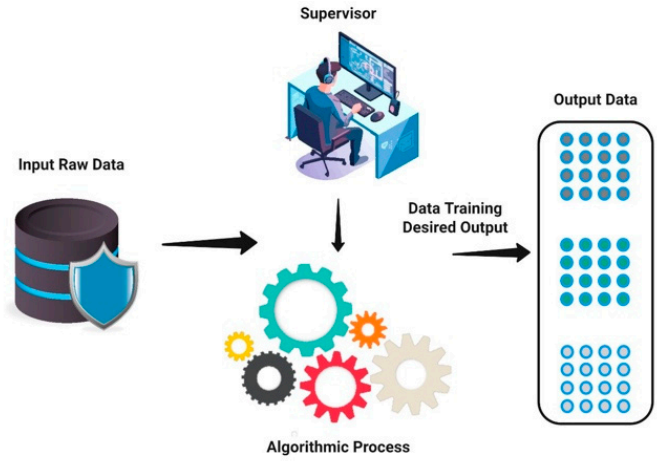
AI/ML technologies will play a crucial role in the 6G communication landscape. Key advancements such as network slicing and traffic management, which significantly enhance network efficiency and dependability, exemplify the utility of AI-driven solutions [107]. Although existing studies predominantly concentrate on the CN, addressing challenges like routing and the development of effective network slicing strategies, there is a notable scarcity of research focused on traffic management and RAN optimization. Furthermore, existing research on traffic management primarily targets the network layer, with limited exploration of the application of AI across the physical, application, or semantic layers. Subsequent sections will illustrate the application of AI/reinforcement learning (RL) and federated learning in this context.

5.1. Types of Machine Learning

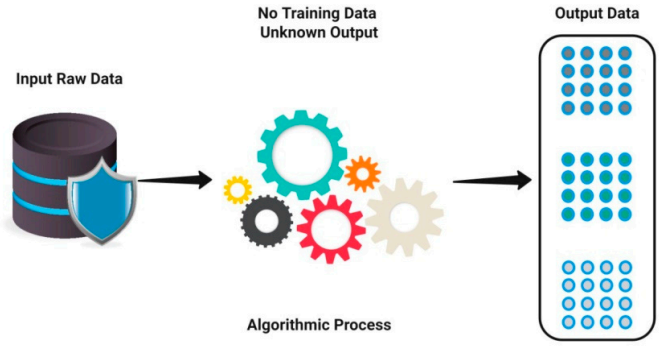
Supervised learning utilizes a dataset composed of input values paired with correct labels, which can be assigned by humans or generated automatically. A standard approach in handling this dataset is to divide it into a training set for model training and a test set for evaluation. This process involves creating a relationship between the input features and their corresponding labels. The primary applications of supervised learning include solving classification and regression tasks [108]. Regression involves predicting a continuous numerical value based on a set of features or predictors through a specific estimation function. In the case of linear regression, the function is linear, whereas logistic regression typically employs a sigmoid function. Classification, on the other hand, aims to predict a categorical label based on input data that has already been categorized. The main distinction from regression is that classification models predict the likelihood of an input belonging to a particular category [109]. Training the model involves using numerous examples from each category, complete with labels, to teach the model how to classify new inputs correctly.

The k-nearest neighbors (k-NN) algorithm assigns a class to an instance by considering the labels of the k-closest neighbors, classifying it into the most frequent category among them [110]. Meanwhile, support vector machines (SVMs) are versatile tools that are used for both classification and regression challenges. They work by plotting data points in an n-dimensional space (with 'n' representing the number of features) and finding the optimal hyperplane that separates the different classes. Decision trees, applicable for both regression and classification, can suffer from high variance due to sensitivity to the training data. To mitigate this, alternative methods like bagging trees, which employ bootstrap aggregation to enhance reliability, are used [111]. Another significant group within supervised learning is artificial neural networks (ANNs), which draw inspiration from the human brain to process, predict, or store information [112]. ANNs consist of neurons and their interconnections, forming the basis of the model. They are applicable to both regression and classification tasks, demonstrating the versatility of supervised learning techniques.

Unsupervised learning stands apart from supervised learning, as illustrated in Figure 10b, because it autonomously seeks to discover a dataset's inherent patterns without the use of labeled data [113]. Instead of relying on external guidance for classification, it endeavors to uncover these labels on its own. The process still distinguishes between training and testing phases, but the input to an unsupervised model includes only the specified number of clusters or features to be extracted. Here, a "cluster" denotes a unique grouping within a dataset for classification purposes.



(**a**)



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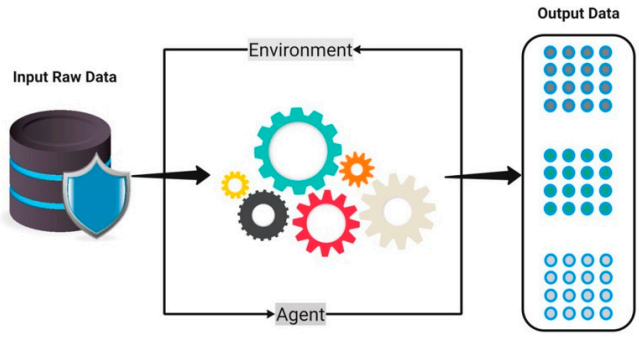

(**c**)

Figure 10. Learning Types: (**a**) supervised learning, (**b**) unsupervised learning, and (**c**) reinforcement learning.

Reinforcement learning conversely uses a learner—usually referred to as an agent—to depict how the system interacts with its environment. The agent's positive results are rewarded, and negative results are penalized. The agent uses this input to guide its learning process and decision-making in a variety of settings. Reinforcement learning aims to maximize the accrual of rewards over a period of time [114]. Figure 10 below shows these three main learning types.

Alnwaimi et al. implemented reinforcement learning (RL) in their study [115] to improve access to the spectrum in femtocell networks. Their strategy entails detecting available spectrum slots and selecting subchannels in a manner that avoids both intra- and inter-tier interference, ensuring compliance with quality of service (QoS) standards. A significant feature of this method is its ability to optimally allocate subcarriers, proving efficient even in small-cell environments. This approach is primarily valued for its swift convergence and rapid decision-making capabilities, albeit at the expense of precision, which is capped at 75%. In another study [116], an RL-based algorithm is employed for selecting the most appropriate frequency channel and deciding on potential location changes in order to mitigate the effects of jamming and substantial interference. This decision process is facilitated by a Q-learning algorithm, with a deep convolutional neural network (CNN) enhancing the speed of channel feature analysis. This methodology excels in environments with a vast number of channels by effectively reducing interference and improving signal-to-noise ratio (SNR) outcomes when compared to traditional Q-learning models that do not utilize CNN.

Furthermore, the research presented in [117] introduces a deep RL framework designed for managing power in 5G heterogeneous networks (HetNets). The objective is to narrow the gap between the throughput requested by mobile users and that which is provided by fine-tuning the power output of macro base stations (BS) or relay nodes (RN). The results indicate that this model achieves optimal user satisfaction in terms of throughput, outperforming conventional techniques such as the water-filling algorithm [118] and the weighted minimum mean-squared error (WMMSE) method [119]. Nonetheless, it is noted that as user demands increase, so does the disparity between requested and allocated throughput.

In reference [120], the researchers introduce a distributed multi-agent deep reinforcement learning (MARL) framework aimed at simultaneously managing user and power distribution within densely populated wireless networks. This framework is informed by real-world data, including measurements and backhaul delays.

Additionally, RL techniques have been applied to address radio resource management (RRM) challenges within 5G satellite communications. Specifically, in study [121], an advanced RL-based algorithm for wireless channel allocation is proposed for use in 5G massive MIMO (m-MIMO).

5.2. Federated Learning and ML

As highlighted in preceding sections, a critical challenge faced by 6G networks is the issue of data overloading, compounded by the constrained storage and computational capacities of user equipment (UE) and base stations (BSs). A contemporary solution that has been proposed involves the adoption of distributed structures specifically for processing purposes, as illustrated in Figure 11. In the context of wireless networks, such distribution is predominantly realized through Multi-access Edge Computing (MEC) architectures. These architectures facilitate cooperation among cloud, edge, and mobile processing layers [122]. The synergy between MEC and machine learning (ML) is fundamental, with MEC leveraging ML techniques within heterogeneous network environments, including 5G and 6G frameworks. The primary aim of MEC is to reduce computation time by strategically distributing traffic across various processing entities.

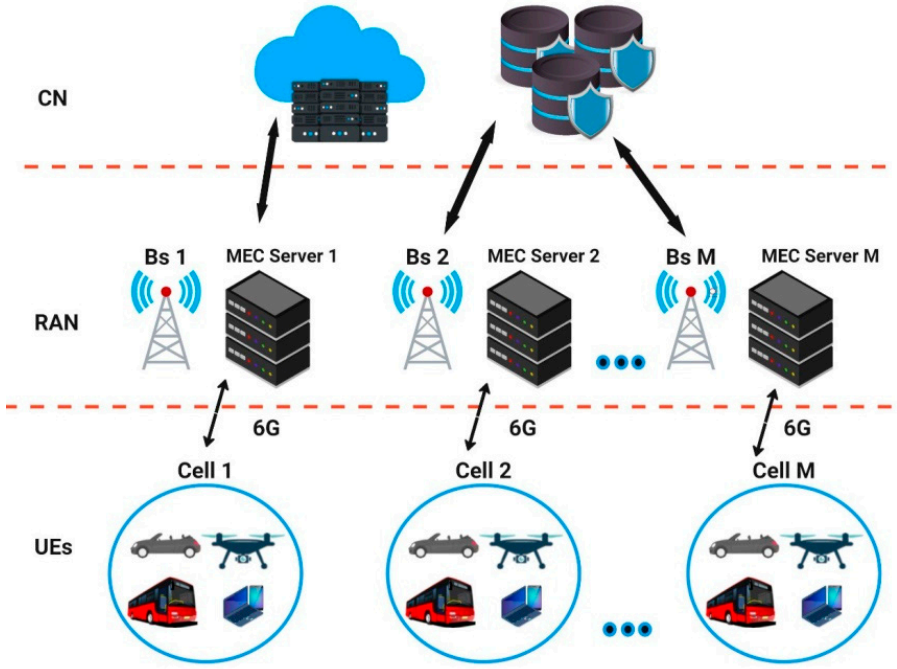

Figure 11. MEC implementation.

As detailed in [123], employing Multi-access Edge Computing (MEC) results in a significant improvement in processing time compared to scenarios devoid of MEC. When a user (denoted as "user x") sends a computational task (referred to as "task i") to an MEC device (labeled as "device y"), the overall latency associated with MEC encompasses several components: the transmission time of task i from user x to device y, the delay experienced by user x while awaiting task processing, and the actual processing time of the task on the MEC device. The integration of MEC with machine learning (ML) extends to solving complex optimization challenges, where it plays a crucial role in addressing resource allocation, beamforming, and caching dilemmas. In this realm, deep learning (DL) models, like artificial neural networks (ANNs), are employed for precise computations. Such endeavors are exemplified in [124], which investigates decentralized hybrid beamforming in 5G next-generation node base stations (gNodeBs).

Furthermore, the collaboration between ML and MEC is exemplified through federated learning (FL). Unlike centralized ML paradigms, which necessitate the upload of local data from user equipment (UEs) to a centralized server, or traditional distributed methods that uniformly distribute data among edge devices, FL employs local data to iteratively train a global model across a network of interconnected edge devices. This process aims to achieve the requisite global accuracy. Local updates from each device are then consolidated at a cloud or MEC server located within base stations (BSs), as depicted in Figure 12. Total training time is a critical aspect in FL model development since achieving the requisite accuracy requires multiple communication cycles between the server and edge devices, which refine the model using their individual local datasets [125]. FL stands out for its efficiency in terms of distributed computing scenarios, primarily due to the enhanced privacy and security afforded by local model training and secure server aggregation. However, challenges arise in radio resource management (RRM) tasks due to the heterogeneity in the processing capabilities, antenna characteristics, and mobility patterns of active UEs or edge devices. This diversity results in non-independent and identically distributed (non-IID) local datasets, characterized by varying labels, features, and volumes. Implementing FL in RRM aims to mitigate these disparities, thereby refining the global model's accuracy.

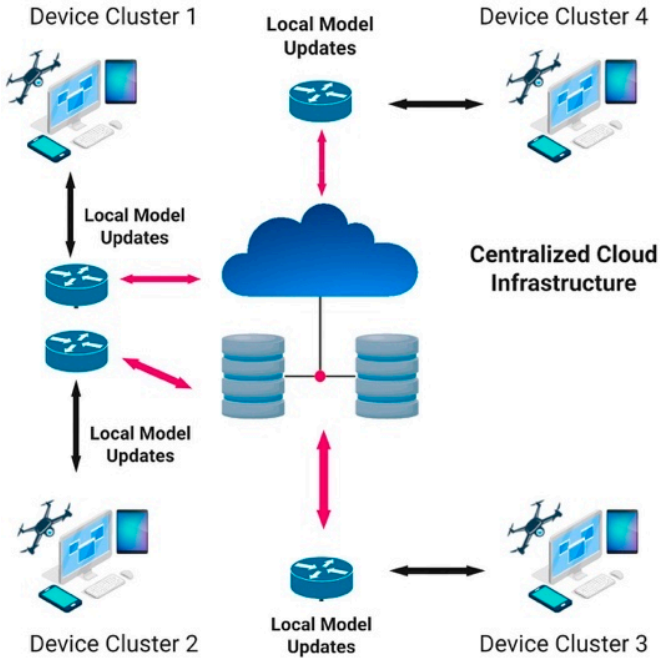

Figure 12. FL in 5G and 6G networks.

Addressing the challenge of training latency across various network topologies, the research in [126] explores a comprehensive optimization strategy that encompasses user selection, frequency allocation, and power distribution.

Within the context of advancing telecommunications infrastructure, both open RAN and cloud RAN architectures are poised to effectively meet the dual objectives of enhancing throughput levels in line with QoS and QoE standards, while also adhering to the principles of low-energy, green networks. The research in [127] give an overview of the evolution of RAN architectures toward 5G and beyond, namely CRAN, vRAN, and O-RAN. It also compares them based on various perspectives, such as edge support, virtualization, control and management, energy consumption, and AI support.

In line with these goals, the study referenced in [128] introduces a deep Q-learning framework tailored for CRAN environments, aiming to maximize energy efficiency (EE). This Q-learning approach leverages historical learning data to anticipate future outcomes and make decisions based on rewards or penalties. However, a common issue encountered is the overestimation of actions, which can limit the probability of achieving the maximum Q-value. To address this, the implementation of a double Q-learning model has been shown to enhance the generation of target Q-values, leading to significant energy savings. A numerical evaluation of this method showed a 22% reduction in energy consumption, while simultaneously improving EE by a comparable margin.

In the context of an O-RAN architecture, the research presented in [129] outlines a reinforcement learning (RL)-based radio resource management (RRM) strategy, which is deployed within the O-RAN ecosystem. This innovative application of RL in an O-RAN setting illustrates the ongoing evolution towards more adaptive, intelligent, and efficient network management solutions capable of meeting the complex demands of modern telecommunications networks.

6. Common Wireless Networks Simulators

In this section, we give a fair and thorough comparison between different wireless simulators that are suitable for simulated CRAN in 5G and 6G, as shown in detail in Table 2.

Table 2. Common Wireless Networks Simulators.

Features	**Vienna 5G SL Simulator [130]**	**Simu5G [131]**	**5G K-Simulator [132]**	**5G-LENA [133]**	**5G-Air-Simulator [134]**
Based Platform	MATLAB	OMNET++	Ns-3	Ns-3	C++
Operating layer	Physical	End-to-end simulator	Split the simulation into four types; a link-level simulator (5G K-SimLink), a system-level simulator (5G K-SimSys), a network simulator (5G K-SimNet), and a highly accessible web-based platform, named 5G K-SimPlatform.	End-to-end simulator	End-to-end simulator
Support dual connectivity	No	Yes	Yes	No	No
Support FDD	No	Yes	No	No	No
Strongest point	Ensure scalability to facilitate the assessment of larger-scale networks in relation to their average performance.	Both frequency division duplexing (FDD) and time-division duplexing (TDD) modes of 5G communications can be simulated, with heterogeneous gNBs (macro, micro, pico, etc.). Dual connectivity with an eNB (LTE base station) and a gNB (5G NR base station) is also available, allowing the simulation of 4G/5G transitions scenarios. Both uplink and downlink resource scheduling with support for carrier aggregation are supported.	It can analyze various aspects of 5G networks through 5G K-SimuLink, 5G K-SimSys, 5G K-SimNet, and 5G K-SimPlatform.	It focuses on simulating the NR MAC and PHY layers and offers instruments for assessing Bandwidth Part management.	It simulates a broad range of common 5G features, including broadcasting and massive MIMO.

Table 2. *Cont.*

Features	Vienna 5G SL Simulator [130]	Simu5G [131]	5G K-Simulator [132]	5G-LENA [133]	5G-Air-Simulator [134]
Weakness point	It is not suitable for assessing multi-layer, end-to-end scenarios.	The 5G RAN and core network's data plane is modeled by Simu5G, not the control plane.	End-to-end simulations are not feasible. Mobility models are not specifically mentioned; only full buffer and non-full buffer application models are available. Furthermore, the ns3 mm-wave module, which was created early in the 5G standardization process, serves as the foundation for the MAC layer.	It does not model dual connectivity, it does not support FDD mode, and there are no signs that it can enable network-controlled D2D connectivity.	It does not have dual 4G/5G or D2D connectivity. Its lack of capabilities for automating the simulation workflow also makes it less useful for large-scale simulations, which is perhaps its most significant drawback.

7. Discussion

This discussion section is organized according to the methods used for allocating resources based on articles that are examined from numerous sources. This review was conducted using resource allocation algorithms and strategies that were implemented by multiple investigators. The data are arranged in accordance with the approaches that are being served by these techniques. Forty research publications met the requirements and were chosen for this study. Each article was examined in light of the problem it addressed and its goals, limitations, and main points of interest. Additionally, as Table 3 illustrates, resource management is performed based on artificial intelligence techniques. The results of the year-wise analysis of articles are shown in Figures 13 and 14. These figures illustrate the total number of articles in each year, such as in 2018, showing the management results without and with artificial intelligence used for resource management.

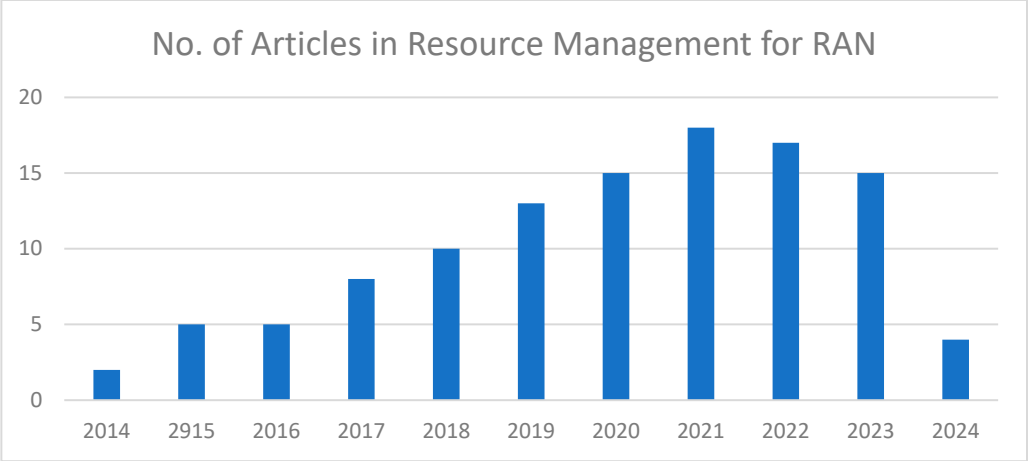

Figure 13. Number of articles in resource management for RAN for the recent ten years.

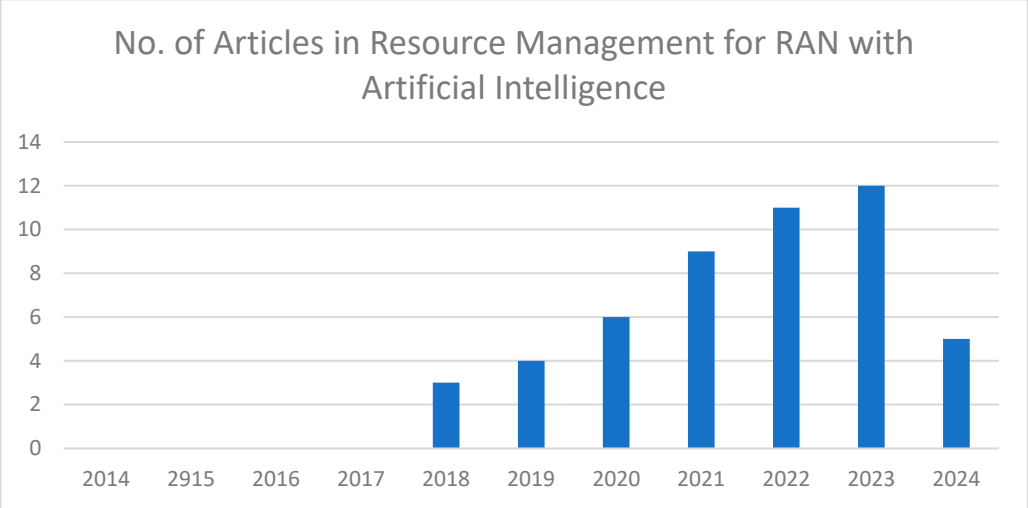

Figure 14. Number of articles in resource management for RAN with artificial intelligent for the recent ten years.

Table 3. Reviewing papers.

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[24]	Recurrent neural networks (RNN) and convolution neural networks (CNN) make up the hybrid quantum deep learning (HQDL) model.	Improve the quality of service (QoS)	Load balancing	Accuracy	Yes	CNN is responsible for network restructuring, allocation of resources, and the gathering of slices, whereas RNN is employed for managing error rates and achieving load balancing.	NS2 and tensor flow
[135]	Bee-Ant-CRANscheme	Both the throughput and the spectral efficiency are improved.	Fronthaul capacity	Throughput	No	Create a logical joint mapping between RRHS and BBUS as well as UE and UE.	MATLAB
[26]	Greedy heuristic	Energy efficiency	BBU capacity and user QoS	Energy efficiency	No	A remote radio head (RRH) group-based mapping (RGBM) strategy designed to reduce power usage within the baseband unit (BBU) pool.	MATLAB
[59]	A particle swarm algorithm (PSO)	Load balancing	Quality of service in terms of number of blocked calls	System performance	No	Suggests an improved RRH-BBU mapping model that aims for a more fair and efficient balance.	Not Defined
[25]	Long Short-Term Memory (LSTM) with recurrent neural networks (RNNs)	Open hardware that provides intelligent radio control for 6 G	Traffic load	Throughput	Yes	Develop a smart scheme for managing radio resources that addresses traffic congestion and validate its effectiveness using a dataset from a major provider.	Not Defined
[136]	EXP3 (exploration and exploitation) and DQL (multi-agent deep Q-learning) are two examples of algorithms that are related to this.	Resource	Resources	Benchmark	Yes	To improve the efficiency of URLLC and eMBB services, suggest a two-timescale RAN slicing mechanism.	PyTorch
[137]	A dynamic neural network (DyNN)-based method	Delay	Complexity	Computing delay	Yes	Examine the issue of orchestrating wireless resources on-demand, with an emphasis on the computational delay encountered during the orchestration decision-making process.	Not Defined

Table 3. *Cont.*

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[138]	A two-dimensional queue	Latency	Traffic load	Delay	No	An analytical investigation and proposal are made for a two-stage queue model.	Not Defined
[139]	Federated deep reinforcement learning approach	Efficient management of RAN slicing	Higher dependence on the environment data	System performance and eost-effectiveness	Yes	Using deep reinforcement learning (DRL), for the automation of management and orchestration in radio access network (RAN) slicing activities.	PyTorch
[140]	Centralized control mechanism	Load balancing	Traffic load	Throughput	No	Provide borrow-and-lend effective dynamic BBU–RRH mapping.	NS-2
[141]	The genetic algorithm (GA) and the K-means clustering algorithm	Optimal deployment of optical fronthaul with the lowest possible overall cost for 5G and beyond cases.	Fronthaul capacity	Cost-effective	No	Passive optical networks (PONs) offer optical technologies that are the most appropriate for networks beyond 5G.	CPLEX
[142]	Discrete Particle Swarm Optimization (EDDPSO)	Load Balancing	Resource and QoS constraints	Load fairness, quality of service, and handover index	No	Linear integer constraints on an optimization problem characterize the dynamic BBU-RRH mapping procedure.	Not Defined
[143]	Federated learning (FL) in RAN to build O-RAN	Quality of service and privacy	Resource	Accuracy	Yes	Provide an intelligence processing in a distributed manner by implementing FL tasks in O-RAN.	Magma
[60]	Integer linear programming (ILP)	Energy efficiency and user association	Quality of service	System cost	No	To benefit from CRAN, each BBU can be actualized by a virtual machine (VM), also known as a virtual BBU (VB). To service clusters of RRHs, VBs can be started and stopped as needed.	CPLEX
[144]	Genetic Algorithm Particle Swarm Optimization	Energy efficiency	Non-linear outage probability formula	Reduces the system outage probability and cost-effective	No	Enhance the smart resource distribution and intelligence in 5G ultra-dense heterogeneous networks through the application of optimization methods and Software-Defined Networking (SDN).	Not Defined

Table 3. *Cont.*

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[145]	Machine learning	Resource	Heterogeneous network	Energy efficiency	Yes	Proposed a new multitier heterogeneous CRAN network for 5G environments, which is a modification of the CRAN design.	Not Defined
[146]	An algorithm based on a bankruptcy game	Resource	User requirement	Resource utilization and Fairness	No	Allocating spectrum resources for cloud RAN slices is the main topic of this work.	Not Defined
[147]	Device-centric architecture	Throughput and delay	Load balancing	Traffic load	No	This paper introduces a device-centric approach to resource allocation specifically designed for device-to-device (D2D) users.	MATLAB
[148]	Threshold-controlled access (TCA) protocol.	Energy efficiency	QoS	Complexity analysis	No	Suggest a new method for allocating uplink resources that allows devices to select resource blocks according to their current battery levels.	MATLAB
[149]	Online Q-learning	Energy efficiency and interferences migrations	QoS	Spectral efficiency (SE) and energy efficiency (EE)	Yes	Using online learning, suggest a centralized resource allocation plan.	Not Defined
[150]	Lyapunov stochastic optimization	Throughput	Fronthaul capacity	Throughput and latency	No	A dual-timescale, fronthaul-conscious SDN control strategy is put forward, wherein the controller aims to optimize the time-averaged throughput of the network.	Not Defined
[151]	Multi-objective optimization techniques	Multi-objective throughput vs. power and delay, vs. cost	Fronthaul capacity	Throughput and delay	No	A new virtualized software-defined cloud radio access network (CRAN) that considers density and employs a multi-objective resource allocation technique is suggested.	Not Defined
[152]	Deep reinforcement learning	Resource utilization	Network traffic	Throughput and rate of packet loss	Yes	A novel approach for real-time scheduling of TDD setup based on dynamic traffic and channel conditions predictions.	TensorFlow/Keras.

Table 3. *Cont.*

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[153]	Deep neural network (DNN)	Data rate, power usage, EE, and signal-to-Interference ratio (SINR)	Resource allocation	Fairness index, throughput, and energy efficiency	Yes	The 5G network introduces machine learning techniques for resource allocation.	Not Defined
[154]	Dynamic priority-based resource allocation	Quality of service	SINR	SNR	No	The proposal outlines a adaptive priority-based resource allocation framework for machine-type communication (MTC) devices.	MATLAB
[155]	Non-convex NP-hard problem	Quality of service (QoS)	Interferences	Throughput and cell load	No	Provide a user association in UDNs.	Not Defined
[58]	Game-Based	Power control	Interferences	Throughput maximization, QoS assurance and interference mitigation	No	In order to handle the interference, suggest a power optimization method for 5G femtocell networks that consists of underlying femtocells and macrocells.	MATLAB
[156]	Location based resource allocation through clustering	Inter-cell interference and data rate	Cell load per cluster	Throughput	No	The study examines a coordinated multi-point scenario, utilizing a collaborative approach among base stations to reduce interference.	MATLAB
[157]	Deep reinforcement learning	Cooperative power distribution and user identification	Quality-of-service (QoS) and wireless backhaul capacity	Energy efficiency	Yes	It is suggested to work directly on the hybrid space, updating the learning strategy and maximizing the average cumulative reward.	Not Defined
[158]	Reinforcement learning	Spectrum efficiency	Interference	Throughput and spectrum efficiency	Yes	Study how the power of a downlink (DL) connection is controlled in UNMNs using various AP kinds.	Not Defined
[43]	Deep learning	Latency and data rate	User association	Computational complexity	Yes	Suggest a deep learning system based on U-Net with the goal of enabling intelligent UE (user equipment) association with rival MBSs and SBSs (small-base stations).	Not Defined

Table 3. *Cont.*

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[159]	Standard deviation of the load distribution	Association of users and load balancing	The number of UEs that each BS is allocated	Network load, throughput	No	Suggest a novel algorithm for associating users with the optimal base station (BS) by taking total network load in the association process.	MATLAB
[160]	Backhaul-aware user association scheme.	User association	Backhaul capacity	Coverage probability	No	Through the implementation of a backhaul-aware user association strategy, semi-closed formulas for network performance indicators are obtained in ultra-dense heterogeneous networks.	Not Defined
[44]	Deep recurrent Q-networks (DRQNs)	Capacity and data rate	User association	Sum-rate gain	Yes	Creating an adaptable and scalable user association method using multi-agent reinforcement learning.	Monte Carlo
[45]	Clustering algorithm and convex optimization problem.	System throughput	Inferences	Inferences and energy efficiency	No	Provide a user association method	Not Defined
[161]	Particle swarm optimization	Energy efficiency (EE)	Both the BSs' load balancing and the DUEs' total transmission power	EE	No	In the context of D2D heterogeneous networks featuring multiple base stations, the combined issue of device-to-device user equipment (DUEs) mode selection, base station choice, channel distribution, and power assignment is explored.	MATLAB
[162]	Two stages: matching game in the first one and a repeated modified English auction.	Spectrum utilization	Interference and user requirements	Channel utilization and the satisfaction level	No	Offers a two-step structure based on auction games and matching theory.	Not Defined
[163]	Two-step genetic algorithm	Energy efficiency	Interference	SE and EE	No	This study creates a resource allocation method for downlink OFDMA in heterogeneous networks (HetNets) that is energy-efficient and based on genetic algorithms (GAs).	Not Defined

Table 3. *Cont.*

Ref.	Algorithms/Techniques	Objectives	Constraints	Performance Measures	Integration of Al	Focus	Simulator Used
[164]	Deep reinforcement learning	Resource utilization	Spectrum	Fairness	No	For the purpose of RAN resource distribution, create a deep reinforcement learning (DRL) with multi-agent framework.	Not Defined
[165]	Federated learning	Network bandwidth and data privacy	Resource	Network load and security robustness	Yes	Examine how federated learning is being deployed	Tensor Flow
[166]	Edge to edge computing	Traffic reduction, low latency, and high security for mobile networks.	Lack of technical preparation for end-to-end (E2E) environments (e.g., devices, RAN, core, applications, human resources) with software/hardware flexibility.	Resource utilization	No	Focus on edge computing and O-RAN	Not Defined

The year-wise analysis of articles form (MDPI, Science Direct, Wiley, Springer, ACM, and IEEE) are shown in Figures 13–16 respectively. These figures are illustrating the total number of articles in each year like in 2018, the management without and with artificial intelligence used for resource management in RAN generally and in cloud RAN specifically.

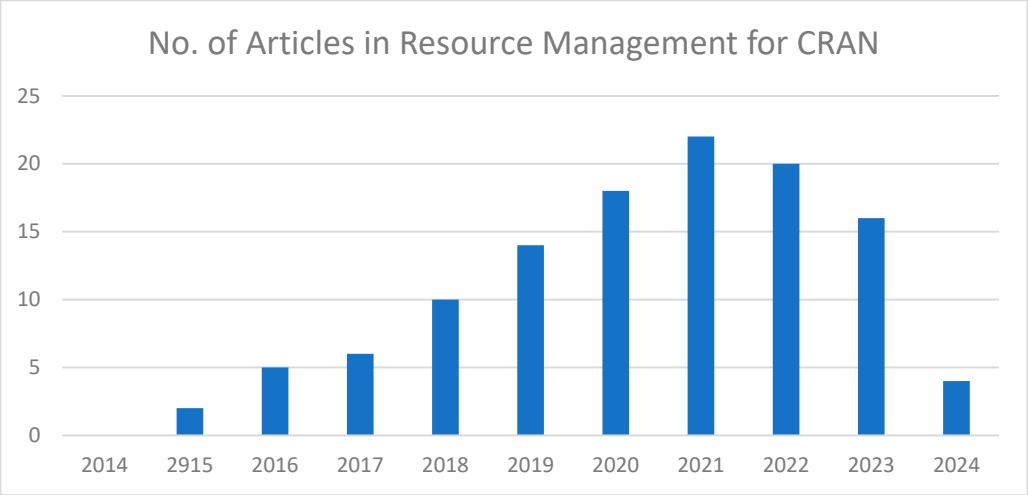

Figure 15. Number of Articles in Resource Management for CRAN for the recent ten years.

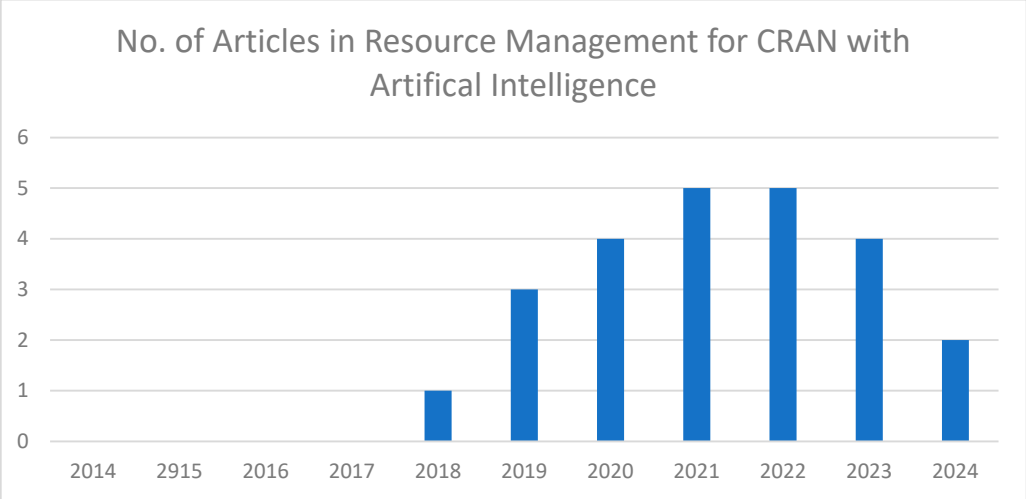

Figure 16. Number of Articles in Resource Management for CRAN with Artificial Intelligent for the recent ten years.

It noted that many papers related to resource management and resource allocation for RAN and cloud RAN are found in IEEE repository as shown in Figures 17 and 18 respectively.

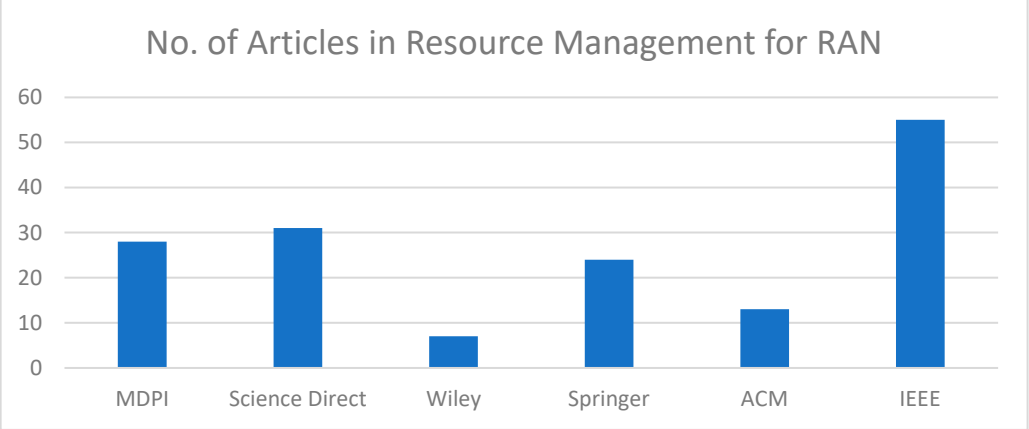

Figure 17. Number of Articles in Resource Management for RAN with respect to source of publishing.

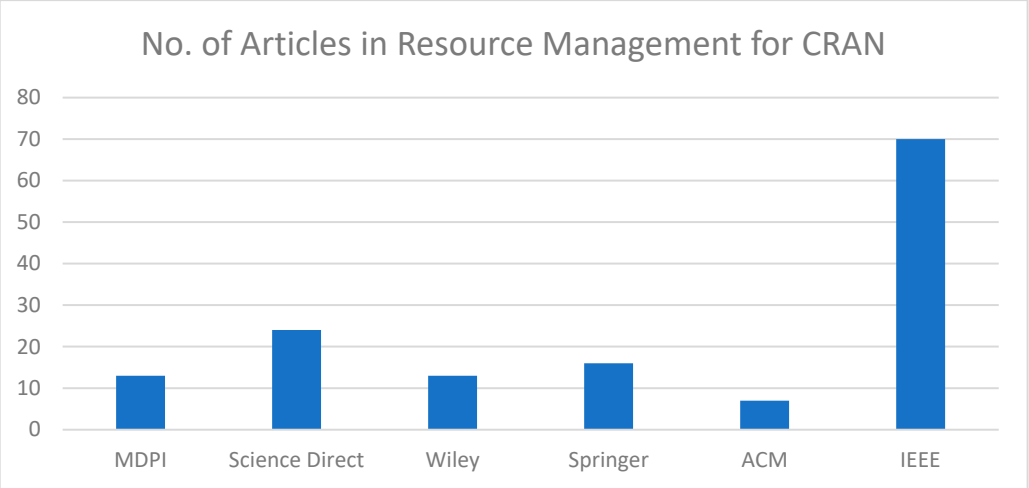

Figure 18. Number of Articles in Resource Management for CRAN with respect to source of publishing.

8. Conclusions

Based on the comprehensive examination of the advancements in CRAN and the integration of AI for resource management within the context of 6G wireless networks, this paper presents a forward-looking perspective on the future of telecommunications infrastructure. It meticulously analyses the current state of CRAN, identifies significant challenges, and proposes AI as a pivotal solution for overcoming these obstacles, thereby enhancing network efficiency, spectrum utilization, and energy conservation. The discussion extends to the evolution of 6G networks, emphasizing the necessity for intelligent, dynamic resource management to meet the increasing demands of futuristic applications and services. The paper contributes to the academic and industrial fields by offering a detailed taxonomy of CRAN resource management and shedding light on the potential of AI to revolutionize 6G networks through improved performance and sustainability. The convergence of CRAN and AI not only promises to address the present limitations but also sets a new direction for the development of ultra-reliable, efficient, and user-centric wireless networks. As we stand on the brink of a new era in telecommunications, this study underscores the importance of continued research and development efforts in integrating AI with CRAN for the successful realization of 6G ambitions.

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List of Abbreviation and Generic Names

RAN	radio access network
CRAN	cloud radio access network
5G	fifth generation of mobile networks
6G	sixth generation of mobile networks
AI	artificial intelligence
NR	new radio
IOT	Internet of Everything
ICT	information and communication technology
uHSLLC	ultra-high-speed, low-latency communications
uMUB	ubiquitous mobile ultra-broadband
uHDD	ultra-high data density
URLLC	ultra-reliable low-latency
eMBB	enhanced mobile broadband
mMTC	massive machine-type communications
EE	energy efficiency
SE	spectrum efficiency
RRH	radio remote head
BBU	baseband unit
CoMP	coordinated multi-point
OPEX	operating expenses
CAPEX	capital expenditures
KPI	key performance indicator
HetNet	heterogeneous networks
UDN	ultra-dense network
RRM	radio resource management
CRM	computational resource management
B5G	beyond fifth generation of mobile networks
QoS	quality of service
QoE	quality of experience
TDD	time-division duplex
FDD	frequency division duplex
UE	user equipment
MEC	mobile edge computing
gNdesBs	base station of fifth generation of mobile networks
eNodeBs	base station of fourth generation of mobile networks
D2D	device-to-device
CRN	cognitive radio network
RL	reinforcement learning
FL	federated learning
NS	network slicing

References

1. Cisco. *Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2017–2022*; White Paper; Cisco: San Jose, CA, USA, 2019.
2. Jabbar, S.Q.; Kadhim, D.J.; Li, Y. Proposed an Adaptive Bitrate Algorithm based on Measuring Bandwidth and Video Buffer Occupancy for Providing Smoothly Video Streaming. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 68–77.
3. Shahraki, A.; Haugen, Ø. Social ethics in internet of things: An outline and review. In Proceedings of the 2018 IEEE Industrial Cyber-Physical Systems (ICPS), St. Petersburg, Russia, 15–18 May 2018; pp. 509–516.

4. Jaber, Z.H.; Kadhim, D.J.; Al-Araji, A.S. Medium access control protocol design for wireless communications and networks review. *Int. J. Electr. Comput. Eng. (IJECE)* **2022**, *12*, 1711–1723. [CrossRef]
5. Shiltagh, N.A.; Al-Raweshidy, H.S. Intelligent Traffic Management and Load Balance Based on Spike ISDN-IoT. *IEEE Syst. J.* **2021**, *15*, 1640–1651.
6. Jiang, D.; Liu, G. An overview of 5G requirements. In *5G Mobile Communications*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 3–26.
7. Gupta, R.; Shukla, A.; Tanwar, S. BATS: A blockchain and AI-empowered drone-assisted telesurgery system towards 6G. *IEEE Trans. Netw. Sci. Eng.* **2020**, *8*, 2958–2967. [CrossRef]
8. Kamal, M.A.; Raza, H.W.; Alam, M.M.; Su'ud, M.M.; Sajak, A. Resource Allocation Schemes for 5G Network: A Systematic Review. *Sensors* **2021**, *21*, 6588. [CrossRef] [PubMed]
9. Swain, S.; Saxena, D.; Kumar, J.; Singh, A.; Lee, C. An AI-driven Intelligent Traffic Management Model for 6G Cloud Radio Access Networks. *IEEE Wirel. Commun. Lett.* **2023**, *12*, 1056–1060. [CrossRef]
10. Faizan, Q. Enhancing QOS Performance of the 5G Network by Characterizing Mm-Wave Channel and Optimizing Interference Cancellation Scheme/Faizan Qamar. Ph.D. Thesis, University of Malaya, Kuala Lumpur, Malaysia, 2019.
11. Kadhim, D.J.; Gong, S.; Liu, W.; Cheng, W. Optimization of Cooperation Sensing Spectrum Performance. In Proceedings of the 2009 WRI International Conference on Communications and Mobile Computing, Kunming, China, 6–8 January 2009.
12. Checko, A.; Christiansen, H.; Yan, Y.; Scolari, L.; Kardaras, G.; Berger, M.; Dittmann, L. Cloud RAN for Mobile Networks—A Technology Overview. *IEEE Commun. Surv. Tutor.* **2015**, *17*, 405–426. [CrossRef]
13. China Mobile Research Institute. *White Paper, Ver. C-RAN: The Road Towards Green RAN*; China Mobile Research Institute: Beijing, China, 2011; Volume 2.
14. Wu, J.; Zhang, Z.; Hong, Y.; Wen, Y. Cloud radio access network (C-RAN): A primer. *IEEE Netw.* **2015**, *29*, 35–41. [CrossRef]
15. Pan, C.; Elkashlan, M.; Wang, J.; Yuan, J.; Hanzo, L. User-centric C-RAN architecture for ultra-dense 5G networks: Challenges and methodologies. *IEEE Commun. Mag.* **2018**, *56*, 14–20. [CrossRef]
16. Luo, J.; Chen, Q.; Tang, L. Reducing power consumption by joint sleeping strategy and power control in delay-aware C-RAN. *IEEE Access* **2018**, *6*, 4655–14667. [CrossRef]
17. Wang, K.; Yang, K.; Magurawalage, C. Joint energy minimization and resource allocation in C-RAN with mobile cloud. *IEEE Trans. Cloud Comput.* **2018**, *6*, 760–770. [CrossRef]
18. Shahraki, A.; Abbasi, M.; Jalil Piran, M.; Taherkordi, A. A Comprehensive Survey on 6G Networks: Applications, Core Services, Enabling Technologies, and Future Challenges. *arXiv* **2021**, arXiv:2101.12475.
19. Alhashimi, H.F.; Hindia, M.N.; Effariza, K.D.; Safie, N.; Qamar, F.; Azrin, K.; Nguyen, Q.N. A Survey on Resource Management for 6G Heterogeneous Networks: Current Research, Future Trends, and Challenges. *Electronics* **2023**, *12*, 647. [CrossRef]
20. Ejaz, W.; Sharma, S.K.; Saadat, S.; Naeem, M.; Anpalagan, A.; Chughtai, N.A. A comprehensive survey on resource allocation for CRAN in 5G and beyond networks. *J. Netw. Comput. Appl.* **2020**, *160*, 102638. [CrossRef]
21. Sharma, N.; Kumar, K. Resource allocation trends for ultra-dense networks in 5G and beyond networks: A classification and comprehensive survey. *Phys. Commun.* **2021**, *48*, 101415. [CrossRef]
22. Manap, S.; Dimyati, K.; Hindia, M.N.; Abu Talip, M.S.; Tafazolli, R. Survey of Radio Resource Management In 5G Heterogeneous Networks. *IEEE Access* **2020**, *8*, 131202–131223. [CrossRef]
23. Yongjun, X.; Gui, G.; Gacanin, H.; Adachi, F. A Survey on Resource Allocation for 5g Heterogeneous Networks: Current Research, Future Trends, and Challenges. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 668–695.
24. Ashwin, M.; Alqahtani, A.S.; Mubarakali, A.; Sivakumar, B. Efficient resource management in 6G communication networks using hybrid quantum deep learning model. *Comput. Electr. Eng.* **2023**, *106*, 108565. [CrossRef]
25. Niknam, S.; Roy, A.; Dhillon, H.S.; Singh, S.; Banerji, R.; Reed, J.H.; Saxena, N.; Yoon, S. Intelligent O-RAN for Beyond 5G and 6G Wireless Networks. *arXiv* **2020**, arXiv:2005.08374.
26. Marzouk, F.; Akhtar, T.; Politis, I.; Barraca, J.P.; Radwan, A. Power Minimizing BBU-RRH Group Based Mapping in C-RAN with Constrained Devices. In Proceedings of the ICC 2020—2020 IEEE International Conference on Communications (ICC), Dublin, Ireland, 7–11 June 2020.
27. Rodoshi, R.T.; Kim, T.; Choi, W. Resource Management in Cloud Radio Access Network: Conventional and New Approaches. *Sensors* **2020**, *20*, 2708. [CrossRef]
28. Khaled, L.; Wei, C.; Yuanming, S.; Jun, Z.; Angela, Z. The roadmap to 6G: AI empowered wireless networks. *IEEE Commun. Mag.* **2019**, *57*, 84–90.
29. Alsabah, M.; Naser, M.A.; Mahmmod, B.M.; Abdulhussain, S.H.; Eissa, M.R.; Al-Baidhani, A.; Noordin, N.K.; Sait, S.M.; Al-Utaibi, K.A.; Hashim, F. 6G Wireless Communications Networks: A Comprehensive Survey. *IEEE Access* **2021**, *9*, 148191–148243. [CrossRef]
30. Vasileios, R.; Sotirios, S.; Panagiotis, S.; Shaohua, W.; George, K.; Sotirios, G. Machine learning in beyond 5G/6G networks—State-of-the-art and future trends. *Electronics* **2021**, *10*, 2786. [CrossRef]
31. Weisi, G. Explainable artificial intelligence (XAI) for 6G: Improving trust between human and machine. *IEEE Commun. Mag.* **2020**, *58*, 39–45.

32. Sulaiman, K.; Suleman, K.; Yasir, A.; Muhammad, K.; Zahid, U.; Shahid, M. Highly accurate and reliable wireless network slicing in 5th generation networks: A hybrid deep learning approach. *J. Netw. Syst. Manag.* **2022**, *30*, 29.
33. Alex, M. Artificial intelligence and cognitive computing for 6G communications & networks. *Int. J. Comput. Sci. Mob. Comput.* **2021**, *10*, 26–31.
34. Gures, E.; Shayea, I.; Ergen, M.; Azmi, M.H.; El-Saleh, A. Machine Learning-Based Load Balancing Algorithms in Future Heterogeneous Networks: A Survey. *IEEE Access* **2022**, *10*, 37689–37717. [CrossRef]
35. Bartsiokas, I.A.; Gkonis, P.K.; Kaklamani, D.I.; Venieris, I.S. ML-Based Radio Resource Management in 5G and Beyond Networks: A Survey. *IEEE Access* **2022**, *10*, 83507–83528. [CrossRef]
36. Iftikhar, S.; Gill, S.S.; Song, C.; Xu, M.; Aslanpour, M.S.; Toosi, A.N.; Du, J.; Wu, H.; Ghosh, S.; Chowdhury, D.; et al. AI-based fog and edge computing: A systematic review, taxonomy and future directions. *Internet Things* **2023**, *21*, 100674. [CrossRef]
37. Nguyen, D. Resource Allocation for Energy Efficiency in 5G Wireless Networks. *EAI Endorsed Trans. Ind. Netw. Intell. Syst.* **2018**, *5*, e1. [CrossRef]
38. Tayyaba, S.; Shah, M. Resource allocation in SDN based 5G cellular networks. *Peer-to-Peer Netw. Appl.* **2019**, *12*, 514–538. [CrossRef]
39. Douik, A.; Dahrouj, H.; Al-Naffouri, T.; Alouini, M. Coordinated scheduling for the downlink of cloud radio-access networks. In Proceedings of the IEEE International Conference on Communications (ICC), London, UK, 8–12 June 2015; pp. 2906–2911.
40. Ali, M.; Rabbani, Q.; Naeem, M.; Qaisar, S.; Qamar, F. Joint user association, power allocation, and throughput maximization in 5G H-CRAN networks. *IEEE Trans. Veh. Technol.* **2017**, *66*, 9254–9262. [CrossRef]
41. Wu, S.; Chao, H.; Ko, C.; Mo, S.; Liang, C.; Cheng, C. Green spectrum sharing in a cloud-based cognitive radio access network. In Proceedings of the Green Computing and Communications (GreenCom), 2013 IEEE and Internet of Things (iThings/CPSCom), IEEE International Conference on and IEEE Cyber, Physical and Social Computing, Beijing, China, 20–23 August 2013; pp. 276–281.
42. Pan, C.; Mehrpouyan, H.; Liu, Y.; Elkashlan, M.; Arumugam, N. Joint pilot allocation and robust transmission design for ultra-dense user-centric TDD C-RAN with imperfect CSI. *IEEE Trans. Wirel. Commun.* **2018**, *17*, 2038–2053. [CrossRef]
43. Zhang, Y.; Xiong, L.; Yu, J. Deep learning-based user association in heterogeneous wireless networks. *IEEE Access* **2020**, *8*, 197439–197447. [CrossRef]
44. Sana, M.; DeDomenico, A.; Yu, W.; Lostanlen, Y.; Strinati, E. Multi-agent reinforcement learning for adaptive user association in dynamic mmWave networks. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 6520–6534. [CrossRef]
45. Zhu, L.; Yang, L.; Zhang, Q.; Zhou, T.; Hua, J. Cluster-based energy-efficient joint user association and resource allocation for B5G ultra-dense network. *Phys. Commun.* **2021**, *46*, 101311. [CrossRef]
46. Shi, Y.; Zhang, J.; Letaief, K. Optimal stochastic coordinated beamforming for wireless cooperative networks with csi uncertainty. *IEEE Trans. Signal Process* **2015**, *63*, 960–973. [CrossRef]
47. Qian, M.; Hardjawana, W.; Shi, J.; Vucetic, B. Baseband processing units virtualization for cloud radio access networks. *IEEE Wirel. Commun. Lett.* **2015**, *4*, 189–192. [CrossRef]
48. Park, S.; Simeone, O.; Sahin, O.; Shamai, S. Performance evaluation of multiterminal backhaul compression for cloud radio access networks. In Proceedings of the 48th IEEE Annual Conference on Information Sciences and Systems (CISS), Princeton, NJ, USA, 19–21 March 2014; pp. 1–6.
49. Lee, Y.; Miyanabe, K.; Nishiyama, H.; Kato, N.; Yamada, T. Threshold-Based RRH Switching Scheme Considering Baseband Unit Aggregation for Power Saving in a Cloud Radio Access Network. *IEEE Syst. J.* **2019**, *13*, 2676–2687. [CrossRef]
50. Fang, F.; Ye, G.; Zhang, H.; Cheng, J.; Leung, V. Energy-efficient joint user association and power allocation in a heterogeneous network. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 7008–7020. [CrossRef]
51. Alsabah, M.; Naser, M.A.; Mahmmod, B.M.; Noordin, N.K.; Abdulhussain, S.H. Sum Rate Maximization Versus MSE Minimization in FDD Massive MIMO Systems with Short Coherence Time. *IEEE Access* **2021**, *9*, 108793–108808. [CrossRef]
52. Awais, M.; Ahmed, A.; Naeem, M.; Iqbal, M.; Ejaz, W.; Anpalagan, A.; Kim, H. Efficient joint user association and resource allocation for cloud radio access networks. *IEEE Access* **2017**, *5*, 1439–1448. [CrossRef]
53. Chen, X.; Li, N.; Wang, J.; Xing, C.; Sun, L.; Lei, M. A dynamic clustering algorithm design for C-RAN based on multi-objective optimization theory. In Proceedings of the IEEE 79th Vehicular Technology Conference (VTC Spring), Seoul, Republic of Korea, 18–21 May 2014; pp. 1–5.
54. Xia, W.; Zhang, J.; Quek, T.; Jin, S.; Zhu, H. Joint optimization of fronthaul compression and bandwidth allocation in heterogeneous CRAN. In Proceedings of the GLOBECOM 2017-2017 IEEE Global Communications Conference, Singapore, 4–8 December 2017; pp. 1–6.
55. Qi, Y.; Imran, M.; Quddus, A.; Tafazolli, R. Achievable rate optimization for coordinated multi-point transmission (CoMP) in cloud-based RAN architecture. In Proceedings of the IEEE International Conference on Communications (ICC), Sydney, NSW, Australia, 10–14 June 2014; pp. 4753–4758.
56. Salhab, N.; Rahim, R.; Langar, R. Throughput-Aware RRHs Clustering in Cloud Radio Access Networks. In Proceedings of the 2018 Global Information Infrastructure and Networking Symposium (GIIS), Thessaloniki, Greece, 23–25 October 2018; pp. 1–5.

57. Mohajer, A.; Sorouri, F.; Mirzaei, A.; Ziaeddini, A.; Rad, K.; Bavaghar, M. Energy-aware hierarchical resource management and Backhaul traffic optimization in heterogeneous cellular networks. *IEEE Syst. J.* **2022**, *16*, 5188–5199. [CrossRef]
58. Pourkabirian, A.; Anisi, M.; Kooshki, F. A game-based power optimization for 5G femtocell networks. *Comput. Commun.* **2021**, *177*, 230–238. [CrossRef]
59. Da Paixao, E.; Vieira, R.; Araujo, W.; Cardoso, D. Optimized load balancing by dynamic BBU-RRH mapping in C-RAN architecture. In Proceedings of the 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC), Barcelona, Spain, 23–26 April 2018; pp. 100–104.
60. Yao, J.; Ansari, N. QoS-Aware Joint BBU-RRH Mapping and User Association in Cloud-RANs. *IEEE Trans. Green Commun. Netw.* **2018**, *2*, 881–889. [CrossRef]
61. Khan, M.; Fakhri, Z.; Al-Raweshidy, H. Semistatic Cell Differentiation and Integration with Dynamic BBU-RRH Mapping in Cloud Radio Access Network. *IEEE Trans. Netw. Servey Manag.* **2018**, *15*, 289–303. [CrossRef]
62. Mouawad, M.; Dziong, Z.; Khan, M. Quality of Service Aware Dynamic BBU-RRH Mapping Based on Load Prediction Using Markov Model in C-RAN. In Proceedings of the 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Halifax, NS, Canada, 30 July–3 August 2018; pp. 1907–1912.
63. Mohammed, S.Q.; Hussein, M.A. Performance Analysis of different Machine Learning Models for Intrusion Detection Systems. *J. Eng.* **2022**, *28*, 61–91. [CrossRef]
64. Pawlicki, M.; Choras, M.; Kozik, R. Defending network intrusion detection systems against adversarial evasion attacks. *Future Gener. Comput. System.* **2020**, *110*, 148–154. [CrossRef]
65. Benzaid, C.; Taleb, T. ZSM security: Threat surface and best practices. *IEEE Netw.* **2020**, *34*, 124–133. [CrossRef]
66. ETSI ISG ZSM, ETSI GS ZSM 002: ZSM Reference Architecture. 2019. Available online: https://www.etsi.org/deliver/etsigs/ZSM/001099/002/01.01.0160/gsZSM002v010101p.pdf (accessed on 11 January 2022).
67. Musumeci, F.; Bellanzon, C.; Carapellese, N.; Tornatore, M.; Pattavina, A.; Gosselin, S. Optimal BBU placement for 5G C-RAN deployment over WDM aggregation networks. *J. Light. Technol.* **2016**, *34*, 1963–1970. [CrossRef]
68. Chen, h.; Li, Y.; Bose, S.; Shao, W.; Xiang, L.; Ma, Y.; Shen, G. Cost-minimized design for TWDM-PON-based 5G mobile backhaul networks. *J. Opt. Commun. Netw.* **2016**, *8*, B1–B11. [CrossRef]
69. Masoudi, M.; Lisi, S.; Cavdar, C. Cost-effective migration toward virtualized C-RAN with scalable fronthaul design. *IEEE Syst. J.* **2020**, *14*, 5100–5110. [CrossRef]
70. Yeganeh, H.; Vaezpour, E. Fronthaul network design for radio access network virtualization from a CAPEX/OPEX perspective. *Ann. Telecommun.* **2016**, *71*, 665–676. [CrossRef]
71. Ha, V.; Le, L.; Dao, N. Energy-efficient coordinated transmission for cloud-rans: Algorithm design and trade-off. In Proceedings of the 48th Annual Conference on Information Sciences and Systems (CISS), Princeton, NJ, USA, 19–21 March 2014; pp. 1–6.
72. Luo, S.; Zhang, R.; Lim, T. Downlink and uplink energy minimization through user association and beamforming in C-RAN. *IEEE Trans. Wirel. Commun.* **2015**, *14*, 494–508. [CrossRef]
73. Peng, M.; Zhang, K.; Jiang, J.; Wang, J.; Wang, W. Energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks. *IEEE Trans. Veh. Technol.* **2015**, *64*, 5275–5287. [CrossRef]
74. Barbarossa, S.; Sardellitti, S.; Di Lorenzo, P. Communicating while computing: Distributed mobile cloud computing over 5G heterogeneous networks. *IEEE Signal Process. Mag.* **2014**, *31*, 45–55. [CrossRef]
75. Liu, A.; Lau, V. Joint power and antenna selection optimization for energy-efficient large distributed MIMO networks. In Proceedings of the IEEE International Conference on Communication Systems (ICCS), Singapore, 21–23 November 2012; pp. 230–234.
76. Hao, W.; Muta, O.; Gacanin, H. Price-based resource allocation in massive MIMO H-CRANs with limited fronthaul capacity. *IEEE Trans. Wirel. Commun.* **2018**, *17*, 7691–7703. [CrossRef]
77. Chughtai, N.; Ali, M.; Qaisar, S.; Imran, M.; Naeem, M.; Qamar, F. Energy efficient resource allocation for energy harvesting aided H-CRAN. *IEEE Access* **2018**, *6*, 43990–44001. [CrossRef]
78. Hao, W.; Chu, Z.; Zhou, F.; Yang, S.; Sun, G.; Wong, K. Green communication for NOMA-based CRAN. *IEEE Internet Things J.* **2019**, *6*, 666–678. [CrossRef]
79. Pappi, K.; Diamantoulakis, P.; Otrok, H.; Karagiannidis, G. Cloud compute-and-forward with relay cooperation. *IEEE Trans. Wirel. Commun.* **2015**, *14*, 3415–3428. [CrossRef]
80. Liu, Q.; Wu, G.; Guo, Y.; Zhang, Y.; Hu, S. Energy efficient resource allocation for control data separated heterogeneous-CRAN. In Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM), Washington, DC, USA, 4–8 December 2016; pp. 1–6.
81. Zhou, Y.; Yu, W.; Toumpakaris, D. Uplink multi-cell processing: Approximate sum capacity under a sum backhaul constraint. In Proceedings of the IEEE Information Theory Workshop (ITW), Seville, Spain, 9–13 September 2013; pp. 1–5.
82. Kim, T.; Chang, J. Profitable and energy-efficient resource optimization for heterogeneous cloud-based radio access networks. *IEEE Access* **2019**, *7*, 34719–34737. [CrossRef]

83. Park, S.; Chae, C.; Bahk, S. Before/after precoding massive MIMO systems for cloud radio access networks. *J. Commun. Netw.* **2013**, *15*, 398–406. [CrossRef]
84. Kalil, M.; Al-Dweik, A.; Sharkh, M.; Shami, A.; Refaey, A. A framework for joint wireless network virtualization and cloud radio access networks for next generation wireless networks. *IEEE Access* **2017**, *5*, 20814–20827. [CrossRef]
85. Amani, N.; Pedram, H.; Taheri, H.; Parsaeefard, S. Energy-efficient resource allocation in heterogeneous cloud radio access networks via BBU offloading. *IEEE Trans. Veh. Technol.* **2019**, *68*, 1365–1377. [CrossRef]
86. Dahrouj, H.; Al-Naffouri, T.; Alouini, M. Distributed cloud association in downlink multicloud radio access networks. In Proceedings of the 2015 49th Annual Conference on Information Sciences and Systems (CISS), Baltimore, MD, USA, 18–20 March 2015; pp. 1–3.
87. Lin, B.; Pan, X.; He, R.; Li, S. Joint wireless-optical infrastructure deployment and layout planning for Cloud-Radio Access Networks. In Proceedings of the International Wireless Communications and Mobile Computing Conference (IWCMC), Nicosia, Cyprus, 4–8 August 2014; pp. 1027–1032.
88. Li, J.; Peng, M.; Cheng, A.; Yuling, Y. Delay-aware cooperative multipoint transmission with backhaul limitation in cloud-RAN. In Proceedings of the IEEE International Conference on Communications Workshops (ICC), Sydney, NSW, Australia, 10–14 June 2014; pp. 665–670.
89. Hong, S.; Kim, J. Joint coding and stochastic data transmission for uplink cloud radio access networks. *IEEE Commun. Lett.* **2014**, *18*, 1619–1622. [CrossRef]
90. Boyd, S.; Lieven, V. *Convex Optimization*; Cambridge University Press: Cambridge, UK, 2004.
91. Cheung, W.C.; Quek, T.Q.S.; Kountouris, M. Throughput. optimization, spectrum. allocation, Throughput optimization spectrum allocation and access control in two-tier femtocell networks. *IEEE J. Sel. Areas Commun.* **2012**, *30*, 561–574.
92. Zhang, X.; Zhang, X.; Han, L. Utilization-oriented spectrum allocation in an underlay cognitive radio network. *IEEE Access* **2018**, *6*, 12905–12912. [CrossRef]
93. Shi, Y.; Zhang, J.; Letaief, K.B. Group sparse beamforming for green cloud-RAN. *IEEE Trans. Wirel. Commun.* **2014**, *13*, 2809–2823.
94. Tao, M.; Chen, E.; Zhou, H.; Yu, W. Content-centric sparse multicast beamforming for cache-enabled cloud RAN. *IEEE Trans. Wirel. Commun.* **2016**, *15*, 6118–6131. [CrossRef]
95. Abdulsaheb, J.A.; Kadhim, D.J. Robot Path Planning in Unknown Environments with Multi-Objectives Using an Improved COOT Optimization Algorithm. *Int. J. Intell. Eng. Syst.* **2022**, *15*, 548–565.
96. Hasan, M.Y.; Kadhim, D.J. A new smart approach of an efficient energy consumption management by using a machine-learning technique. *Indones. J. Electr. Eng. Comput. Sci.* **2022**, *25*, 68–78. [CrossRef]
97. Sadr, S.; Adve, R.S. Partially distributed resource allocation in small-cell networks. *IEEE Trans. Wirel. Commun.* **2014**, *13*, 6851–6862. [CrossRef]
98. Zhang, Y.; Wang, S.; Guo, J. Clustering-based interference management in densely deployed femtocell networks. In Proceedings of the IEEE/CIC ICCC Symposium on Wireless Networking and Multimedia, Shenzhen, China, 2–4 November 2015; pp. 478–483.
99. Huang, H.; Trivellato, M.; Hottinen, A.; Shafi, M.; Smith, P.J.; Valenzuela, R. Increasing downlink cellular throughput with limited network MIMO coordination. *IEEE Trans. Wirel. Commun.* **2009**, *8*, 2983–2989. [CrossRef]
100. Guo, Y.; Ma, J.; Wang, C.; Yang, K. Incentive-based optimal nodes selection mechanism for threshold key management in MANETs with selfish nodes. *Int. J. Distrib. Sens. Netw.* **2013**, *9*, 416983. [CrossRef]
101. Blumrosen, L.; Nisan, N. Combinatorial auctions. In *Algorithmic Game Theory*; Cambridge University Press: Cambridge, UK, 2007; pp. 267–298.
102. Cho, J.; Swami, A.; Cook, T. Combinatorial auction-based multiple dynamic mission assignment. In Proceedings of the IEEE Military Communications Conference, Baltimore, MD, USA, 7–10 November 2011; pp. 1327–1332.
103. Ferdouse, L.; Das, O.; Anpalagan, A. Auction based distributed resource allocation for delay aware OFDM based cloud-RAN system. In Proceedings of the IEEE Global Communications Conference, Singapore, 4–8 December 2017; pp. 1–6.
104. Fan, S.; Tian, H. Cooperative resource allocation for self-healing in small cell networks. *IEEE Commun. Lett.* **2015**, *19*, 1221–1224. [CrossRef]
105. Bai, Z.; Ma, L.; Dong, Y.; Ma, P. Energy-efficient resource allocation for secure cognitive radio network with delay QoS guarantee. *IEEE Syst. J.* **2019**, *13*, 2795–2805. [CrossRef]
106. Al-Tayar, D.; Alisa, Z. Finding the Optimal Shortest Path in Stochastic Networks Using the Markov Decision Process (MDP). *Inf. Sci. Lett. Int. J.* **2023**, *12*, 2811–2825.
107. Clemm, A.; Vega, M.T.; Ravuri, H.K.; Wauters, T.; De Turck, F. Toward truly immersive holographic-type communication: Challenges and solutions. *IEEE Commun. Mag.* **2020**, *58*, 93–99. [CrossRef]
108. Hassan, A.Y.; Saleh, M.H. Intelligence framework dust forecasting using regression algorithms models. *Indones. J. Electr. Eng. Comput. Sci.* **2023**, *32*, 177–184. [CrossRef]
109. Berardinelli, G.; Mahmood, N.H.; Rodriguez, I.; Mogensen, P. Beyond 5G wireless IRT for industry 4.0: Design principles and spectrum aspects. In Proceedings of the IEEE Global Communications Conference Workshops (GC Wkshps), Abu Dhabi, United Arab Emirates, 9–13 December 2018; pp. 1–6.
110. Zhang, Q.; Liu, J.; Zhao, G. Towards 5G enabled tactile robotic telesurgery. *arXiv* **2018**, arXiv:1803.03586.

111. Den Berg, D.; Glans, R.; De Koning, D.; Kuipers, F.A.; Lugtenburg, J.; Polachan, K.; Venkata, P.T.; Singh, C.; Turkovic, B.; Van Wijk, B. Challenges in haptic communications over the tactile internet. *IEEE Access* **2017**, *5*, 502–518. [CrossRef]
112. Rashid, M.M.; Shiltagh, N.A. Automatic Spike Neural Technique for Slicing Bandwidth Estimated Virtual Buffer-Size in Network Environment. *J. Eng.* **2023**, *29*, 87–97.
113. Morocho-Cayamcela, M.E.; Lee, H.; Lim, W. Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions. *IEEE Access* **2019**, *7*, 137184–137206. [CrossRef]
114. Cayamcela, M.E.M.; Lim, W. Artificial intelligence in 5G technology: A survey. In Proceedings of the International Conference Information Communication Technology Converge. (ICTC), Jeju-Si, Republic of Korea, 17–19 October 2018; pp. 860–865.
115. Alnwaimi, G.; Vahid, S.; Moessner, K. Dynamic heterogeneous learning games for opportunistic access in LTE-based macro/femtocell deployments. *IEEE Trans. Wirel. Commun.* **2015**, *14*, 2294–2308. [CrossRef]
116. Han, G.; Xiao, L.; Poor, H.V. Two-dimensional anti-jamming communication based on deep reinforcement learning. In Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), New Orleans, LA, USA, 5–9 March 2017; pp. 2087–2091.
117. Spantideas, A.S.G.; Tsinos, C.; Trakadas, P. Power control in 5G heterogeneous cells considering user demands using deep reinforcement learning. In Proceedings of the International Conference on Artificial Intelligence Applications and Innovations (IFIP), Creta, Greece, 25–27 June 2021; Springer: Cham, Switzerland, 2021; pp. 95–105.
118. Qi, Q.; Minturn, A.; Yang, Y. An efficient water-filling algorithm for power allocation in OFDM-based cognitive radio systems. In Proceedings of the International Conference on Systems and Informatics (ICSAI), Yantai, China, 19–20 May 2012; pp. 2069–2073.
119. Baligh, H.; Hong, M.; Liao, W.-C.; Luo, Z.-Q.; Razaviyayn, M.; Sanjabi, M.; Sun, R. Cross-layer provision of future cellular networks: A WMMSE-based approach. *IEEE Signal Process. Mag.* **2014**, *31*, 56–68. [CrossRef]
120. Naderializadeh, N.; Sydir, J.J.; Simsek, M.; Nikopour, H. Resource management in wireless networks via multi-agent deep reinforcement learning. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 3507–3523. [CrossRef]
121. Guan, M.; Wu, Z.; Cui, Y.; Cao, X.; Wang, L.; Ye, J.; Peng, B. 'An intelligent wireless channel allocation in HAPS 5G communication system based on reinforcement learning. *EURASIP J. Wirel. Commun. Netw.* **2019**, *2019*, 138. [CrossRef]
122. Le, N.T.; Hossain, M.A.; Islam, A.; Kim, D.; Choi, Y.; Jang, Y.M. Survey of promising technologies for 5G networks. *Mob. Inf. Syst.* **2016**, *2016*, 2676589. [CrossRef]
123. Ning, Z.; Wang, X.; Rodrigues, J.J.; Xia, F. Joint computation offloading, power allocation, and channel assignment for 5G-enabled traffic management systems. *IEEE Trans. Ind. Inf.* **2019**, *15*, 3058–3067. [CrossRef]
124. Elbir, A.M. CNN-based precoder and combiner design in mmWave MIMO systems. *IEEE Commun. Lett.* **2019**, *23*, 1240–1243. [CrossRef]
125. Zhang, C.; Xie, Y.; Bai, B.; Yu, B.; Li, W.; Gao, Y. A survey on federated learning. *Knowl.-Based Syst.* **2021**, *216*, 106775. [CrossRef]
126. Zhao, L.; Xu, H.; Wang, J.; Chen, Y.; Chen, X.; Wang, Z. Computation–communication resource allocation for federated learning system with intelligent reflecting surfaces. *Arab. J. Sci. Eng.* **2022**, *2022*, 10203–10209. [CrossRef]
127. Brik, B.; Boutiba, K.; Ksentini, A. Deep Learning for B5G Open Radio Access Network: Evolution, Survey, Case Studies, and Challenges. *IEEE Open J. Commun. Soc.* **2022**, *3*, 228–250. [CrossRef]
128. Iqbal, A.; Tham, M.-L.; Chang, Y.C. Double deep Q-network-based energy-efficient resource allocation in Cloud Radio Access Network. *IEEE Access* **2021**, *9*, 20440–20449. [CrossRef]
129. Mungari, F. An RL approach for radio resource management in the O-RAN architecture. In Proceedings of the 18th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), Rome, Italy, 6–9 July 2021; pp. 1–2.
130. Müller, M.K.; Ademaj, F.; Dittrich, T.; Fastenbauer, A.; Elbal, B.R.; Nabavi, A.; Nagel, L.; Schwarz, S.; Rupp, M. Flexible multi-node simulation of cellular mobile communications: The Vienna 5G system level simulator. *EURASIP J. Wirel. Commun. Netw.* **2018**, *2018*, 227. [CrossRef]
131. Nardini, G.; Sabella, D.; Stea, G.; Thakkar, P.; Virdis, A. Simu5G–An OMNeT++ Library for End-to-End Performance Evaluation of 5G Networks. *IEEE Access* **2020**, *8*, 181176–181191. [CrossRef]
132. Kim, Y.; Bae, J.; Lim, J.; Park, E.; Baek, J.; Han, S.I.; Chu, C.; Han, Y. 5G K-simulator: 5G system simulator for performance evaluation. In Proceedings of the IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), Seoul, Republic of Korea, 22–25 October 2018; pp. 1–2.
133. Patriciello, N.; Lagen, S.; Bojovic, B.; Giupponi, L. An E2E simulator for 5G NR networks. Simulation Model. *Pract. Theory* **2019**, *96*, 101933. [CrossRef]
134. Martiradonna, S.; Grassi, A.; Piro, G.; Boggia, G. 5G-air-simulator: An open-source tool modeling the 5G air interface. *Comput. Netw.* **2020**, *173*, 107151. [CrossRef]
135. Ari, A.; Gueroui, A.; Titouna, C.; Thiare, O.; Aliouat, Z. Resource allocation scheme for 5G C-RAN: A Swarm Intelligence based approach. *Comput. Netw.* **2019**, *165*, 106957. [CrossRef]
136. Filali, A.; Mlika, Z.; Cherkaoui, S.; Kobbane, A. Dynamic SDN-based Radio Access Network Slicing with Deep Reinforcement Learning for URLLC and eMBB Services. *arXiv* **2022**, arXiv:2202.06435. [CrossRef]
137. Ma, L.; Cheng, N.; Wang, X.; Sun, R.; Lu, N. On-Demand Resource Management for 6G Wireless Networks Using Knowledge-Assisted Dynamic Neural Networks. *arXiv* **2022**, arXiv:2208.01785.

138. Louvros, S.; Paraskevas, M.; Chrysikos, T. QoS-Aware Resource Management in 5G and 6G Cloud-Based Architectures with Priorities. *Information* **2023**, *14*, 175. [CrossRef]
139. Abouaomar, A.; Taik, A.; Filali, A.; Cherkaoui, S. Federated Deep Reinforcement Learning for Open RAN Slicing in 6G Networks. *arXiv* **2022**, arXiv:2206.11328. [CrossRef]
140. Chen, Y.; Chiang, W.; Shih, M. A Dynamic BBU–RRH Mapping Scheme Using Borrow-and-Lend Approach in Cloud Radio Access Networks. *IEEE Syst. J.* **2017**, *12*, 1632–1643. [CrossRef]
141. Fayad, A.; Cinkler, T.; Rak, J.; Jha, M. Design of Cost-Efficient Optical Fronthaul for 5G/6G Networks: An Optimization Perspective. *Sensors* **2022**, *22*, 9394. [CrossRef] [PubMed]
142. Khan, M.; Sabir, F.A.; Al-Raweshidy, H.S. Load Balancing by Dynamic BBU-RRH Mapping in a Self-Optimised Cloud Radio Access Network. In Proceedings of the IEEE International Conference on Telecommunications (ICT), Limassol, Cyprus, 3–5 May 2017.
143. Firouzi, R.; Rahmani, R. 5G-Enabled Distributed Intelligence Based on O-RAN for Distributed IoT Systems. *Sensors* **2023**, *23*, 133. [CrossRef] [PubMed]
144. Zhao, Y.; Chen, Y.; Jian, R.; Yang, L. A Resource Allocation Scheme for SDN-based 5G Ultra-Dense Heterogeneous Networks. In Proceedings of the IEEE Globecom Workshops, Singapore, 4–8 December 2017.
145. Bashir, A.K.; Arul, R.; Basheer, S.; Raja, G.; Jayaraman, R.; Qureshi, N. An optimal multitier resource allocation of cloud RAN in 5G using machine learning. *Trans. Emerg. Telecommun. Technol.* **2019**, *30*, e3627. [CrossRef]
146. Jia, Y.; Tian, H.; Fan, S.; Zhao, P.; Zhao, K. Bankruptcy game-based resource allocation algorithm for 5G Cloud-RAN slicing. In Proceedings of the 2018 IEEE Wireless Communications and Networking Conference (WCNC), Barcelona, Spain, 15–18 April 2018.
147. Mishra, P.K.; Pandey, S.; Udgata, S.K.; Biswash, S.K. Device-Centric Resource Allocation Scheme for 5G Networks. *Phys. Commun.* **2018**, *26*, 175–184. [CrossRef]
148. Ali, A.; Shah, G.A.; Arshad, J. Energy Efficient Resource Allocation for M2M Devices in 5G. *Sensors* **2019**, *19*, 1830. [CrossRef] [PubMed]
149. AlQerm, I.; Shihada, B. Enhanced Machine Learning Scheme for Energy Efficient Resource Allocation in 5G Heterogeneous Cloud Radio Access Networks. In Proceedings of the IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Montreal, QC, Canada, 8–13 October 2017.
150. Liu, C.; Samarakoon, S.; Bennis, M.; Vincent Poor, H. Fronthaul-Aware Software-Defined Wireless Networks: Resource Allocation and User Scheduling. *IEEE Trans. Wirel. Commun.* **2018**, *17*, 533–547. [CrossRef]
151. Baghani, M.; Parsaeefard, S.; Le-Ngoc, T. Multi-Objective Resource Allocation in Density Aware Designed of C-RAN in 5G. *IEEE Access* **2018**, *6*, 45177–45190. [CrossRef]
152. Tang, F.; Zhou, Y.; Kato, N. Deep Reinforcement Learning for Dynamic Uplink/Downlink Resource Allocation in High Mobility 5G HetNet. *IEEE J. Sel. Areas Commun.* **2020**, *38*, 2773–2782. [CrossRef]
153. Purushothaman, K.E.; Nagarajan, V. Evolutionary Multi-Objective Optimization Algorithm for Resource Allocation Using Deep Neural Network in 5G Multi-User Massive MIMO. *Int. J. Electron.* **2021**, *108*, 1214–1233. [CrossRef]
154. Rehman, W.U.; Salam, T.; Almogren, A.; Haseeb, K.; Din, I.U.; Bouk, S.H. Improved Resource Allocation in 5G MTC Networks. *IEEE Access* **2020**, *8*, 49187–49197. [CrossRef]
155. Si, Z.; Chuai, G.; Gao, W.; Zhang, J.; Chen, X.; Zhang, K. A QoS-based joint user association and resource allocation scheme in ultra-dense networks. *EURASIP J. Wirel. Commun. Netw.* **2021**, *2021*, 2. [CrossRef]
156. Kim, S.-J.; Kim, J.-G. Location-Based Resource Allocation in Ultra-Dense Network with Clustering. *Sensors* **2021**, *21*, 4022. [CrossRef] [PubMed]
157. Hsieh, C.-K.; Chan, K.-L.; Chien, F.-T. Energy-Efficient Power Allocation and User Association in Heterogeneous Networks with Deep Reinforcement Learning. *Appl. Sci.* **2021**, *11*, 4135.
158. Li, Y.; Tang, Z.; Lin, Z.; Gong, Y.; Du, X.; Guizani, M. A Reinforcement Learning Power Control Algorithm Based on Graph Signal Processing for Ultra-dense Mobile Networks. *IEEE Trans. Netw. Sci. Eng.* **2020**, *8*, 2694–2705. [CrossRef]
159. Hassan, N.; Fernando, X. An Optimum User Association Algorithm in Heterogeneous 5G Networks Using Standard Deviation of the Load. *Electronics* **2020**, *9*, 1495. [CrossRef]
160. Yu, J.; Zhang, H.; Chen, Y.; Ruan, Y. Performance Analysis of Backhaul-Aware User Association in 5G Ultradense Heterogeneous Networks. *Wirel. Commun. Mob. Comput.* **2021**, *2021*, 8879690. [CrossRef]
161. Kuang, Z.; Li, G.; Zhang, L.; Zhou, H.; Li, C.; Liu, A. Energy Efficient Mode Selection, Base Station Selection and Resource Allocation Algorithm in D2D Heterogeneous Networks. *Peer-to-Peer Netw. Appl.* **2020**, *13*, 1814–1829. [CrossRef]
162. Rostom, M.A.; Abd El-Malek, A.H.; Abo-Zahhad, M.; Elsabrouty, M.M. A Two-Stage Matching Game and Repeated Auctions for Users Admission and Channels Allocation in 5G HetNets. *IEEE Access* **2022**, *11*, 17739–17754. [CrossRef]
163. Qi, X.; Khattak, S.; Zaib, A.; Khan, I. Energy Efficient Resource Allocation for 5G Heterogeneous Networks Using Genetic Algorithm. *IEEE Access* **2021**, *9*, 160510–160520. [CrossRef]
164. Rezazadeh, F.; Zanzi, L.; Devoti, F.; Barrachina-Muñoz, S.; Zeydan, E.; Costa-Pérez, X.; Mangues-Bafalluy, G. A Multi-Agent Deep Reinforcement Learning Approach for RAN Resource Allocation in O-RAN. In Proceedings of the IEEE INFOCOM 2023—IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Hoboken, NJ, USA, 20 May 2023.

165. Firouzi, R.; Rahmani, R.; Kanter, T. Federated Learning for Distributed Reasoning on Edge Computing. *Procedia Comput. Sci.* **2021**, *184*, 419–427. [CrossRef]
166. Nakazato, J.; Kuchitsu, M.; Pawar, A.; Masuko, S.; Tokugawa, K.; Kubota, K.; Maruta, K.; Sakaguchi, K. Proof-of-Concept of Distributed Optimization of Micro-Services on Edge Computing for Beyond 5G. In Proceedings of the IEEE 95th Vehicular Technology Conference: (VTC2022-Spring), Helsinki, Finland, 19–22 June 2022; pp. 1–6.

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