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Survey of Radio Resource Management in 5G Heterogeneous Networks

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ABSTRACT Radio resource management (RRM) for future fifth-generation (5G) heterogeneous networks (HetNets) has emerged as a critical area due to the increased density of small-cell networks and radio access technologies. Recent research has mostly concentrated on resource management, including spectrum utilization and interference mitigation, but the complexities of these resources have been given little attention. This paper provides an overview of the issues arising from future 5G systems and highlights their importance. The different approaches used in recently published surveys categorizing RRM schemes are discussed, and the survey method is presented. We report on a survey of HetNet RRM schemes that have been studied recently, with a focus on the joint optimization of radio resource allocation with other mechanisms. These RRM schemes were subcategorized according to their optimization metrics and qualitatively analyzed and compared. An analysis of the complexity of RRM schemes in terms of implementation and computation is presented. Several potential scopes of research for future RRM in 5G HetNets are also identified.

INDEX TERMS Computational complexity, heterogeneous networks, radio resource management.

I. INTRODUCTION

The 5G New Radio (NR) system is driven by the demand for large volumes of data due to the popularity of data-hungry applications for mobile devices. These applications include augmented reality (AR) and virtual reality (VR) applications in games and audio and video streaming (e.g., Netflix, Spotify and YouTube) services that are widely used by consumers. Moreover, the sophisticated technology for smartphone displays that enables users to view videos at high definition has increased the demand for greater data capacity. According to Ericsson's Mobility Report in June 2019, worldwide data traffic from videos in mobile networks will reach 75% of the total mobile data in 2024, compared to only 60% in 2018 [1]. The 5G system is expected to increase the volume of data by 1,000 times (traffic volume at tens of Tbps/km^2), decrease latency by five times (ultralow latency at the millisecond level), increase connectivity with other devices 100-fold, increase the sum of the data rate (10 Gbps peak data rate), increase battery performance 10-fold (low power consumption), and improve reliability by 100% [2]–[5]. This network will connect people as well as vehicles, machines, and apparatuses, and can enable new services and user experiences. It will make mission-critical control applications attainable through low-latency communication links such as vehicle-to-vehicle (V2V) communications and the connection of the enormous number of Internet of Things (IoT) devices. In achieving these demands, some of the key technologies identified in the 5G protocol include massive multiple-input multiple-output (MIMO) implementation, millimeter wave (mmWave) transmissions, ultradense networks (UDNs), and multi-tier HetNets [6]–[9].

Massive MIMO technology can achieve higher spectral and energy efficiency than the traditional single-input single-output (SISO) technique [7], [8]. The system is made up of a large number of small antennas that can increase capacity linearly with the number of antennas at the base station (BS) or user equipment (UE). It was designed to simultaneously

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serve many UEs in the same time-frequency resources by employing spatial multiplexing to improve the spectral efficiency (SE). It can also increase energy efficiency (EE) by using beamforming techniques, through which the signal from the antenna is directed to the user, which will suppress interference and improve data link reliability [10], [11].

The existing ultrahigh frequency (UHF) wireless network design will not be able to cater to 5G needs since the spectra available in 300 MHz to 3 GHz are almost fully occupied and have nearly reached the Shannon limit [12]–[14]. One way of solving spectrum unavailability is to explore the utilization of higher frequency spectra from 3 GHz to 300 GHz. There are wide frequency bands that have the potential to be utilized, except for 57 GHz to 64 GHz and 164 GHz to 200 GHz. These bands are not suitable for wireless communication, as signals at those frequencies can be absorbed by oxygen and water vapor [5], [15]. In addition, there are ongoing works on terahertz (THz) frequency bands from 300 GHz to 3 THz, which can provide even wider bandwidths to accommodate future applications with extremely high data rates [16], [17]. Working in higher frequency bands means that the operating wavelength is in the mmWave, and the radio networking for mmWave will be very different from existing wireless networks. For mmWave signals, the path losses, signal penetration, and blocking effects are high [18], [19]; hence, the importance of reflection, scattering and line-of-sight (LOS) propagation is more significant [5], [15], [20]. Therefore, it is necessary to decrease the distance between users and access nodes operating at the mmWave, making the small-cell network an optimal solution. These small-cell networks will be able to expand the coverage for every unit area via deployment in a highly concentrated manner to increase the network capacity [9], [21], [22], which requires an ultradense network.

When the densification of small-cell networks is allowed, more users can be served in an area that shares the same spectrum, making higher SE achievable. The total power consumption of the UEs can also be reduced because minimal power transmission is needed to communicate with nearby small cells. The small-cell network was first introduced in Long-Term Evolution (LTE) Release 9, which featured low power consumption and was proposed for use in smaller coverage areas such as homes, offices, and shopping malls [23], [24]. Small-cell networks can be categorized into three main categories: femtocells, pico cells and relay nodes (RNs). A femtocell is the smallest unit that is usually deployed indoors for residential use and is typically operated by homeowners in an uncoordinated manner from a macrocell network. The typical coverage radius for a femtocell network ranges from 10 to 30 meters using less than 100 mWatt for transmission, and the network is backhauled by fiber or digital subscriber line (DSL) cables. Pico cell networks, with power consumption from 0.25 to 2 Watts, are deployed by mobile network operators (MNOs) to improve the outdoor coverage of an existing cellular network (consisting of macrocells and microcells). A pico cell network can provide coverage up to a 100-meter radius and is used for larger indoor environments such as shopping malls and airports [23], [25]. RNs are deployed by MNOs at the edge of a cell network or at dead-zone areas, where the signal strength from a macrocell network is weak or not available. Through deployment of RNs, the coverage and throughput can be enhanced, and a balanced traffic load between users at the cell edge and cell center can be achieved [14], [26]. This mixture of network operations between an existing macrocell network together with the dense deployment of small cells is known as a HetNet. The deployment of various types of small-cell networks can be visualized as a multi-tier HetNet, as shown in Fig. 1. Although small-cell networks are already in use in the existing cellular network, the future 5G HetNet will have a higher density of these small cells to the extent of having one femtocell network in every room of a building. This is necessary to achieve the high capacity and massive connectivity requirements for 5G. The new HetNet is expected to combine multiple radio access technologies (RATs) such as 2G, 3G, LTE-Advanced (LTE-A), WiFi, and Device-to-Device (D2D) communications to support various applications. It will also isolate the indoor and outdoor technologies; indoor small-cell networks will use mmWave technology whereas the outdoor environment will make use of massive MIMO [27] technology. The 3rd Generation Partnership Project (3GPP) Release 12 specified some potential technologies in the 5G HetNet, such as the dual connectivity (DC) feature that allows for users to connect to both macrocell and small-cell networks at the same time using the same or different carrier frequencies [14], [28], [29]. The DC feature is expected to enhance the considerable data rate for the overall HetNet.

With these mixed technologies in HetNets, future mobile devices will be equipped with multiple radio interfaces to enable users to take advantage of these RATs and seamlessly switch between technologies. However, there are cautions concerning implementation. The RRM of the 5G HetNet will be more complex than the previous LTE-A, and it is critical to handle resources efficiently. Additionally, with the deployment of uncoordinated femtocell networks by privately owned buildings or residential properties, the interference management of HetNets will become more complicated. For example, a UE in a HetNet may receive interference from macrocell base stations (MBSs), UEs, and small-cell base stations (SBSs) at a different tier. This will worsen if the deployed femtocell BS uses the same spectrum as the macrocell BS. In addition to RRM and interference management concerns, there are several other equally important issues such as power allocation, user association, fairness, allocated capacity, and complexity. These issues are detailed in Section II along with recent methods and techniques to handle related problems.

A. CONTRIBUTIONS OF THE SURVEY

Prior to this work, several survey papers extensively discussed radio resource management considering various wireless system aspects. A survey on RRM schemes focused on

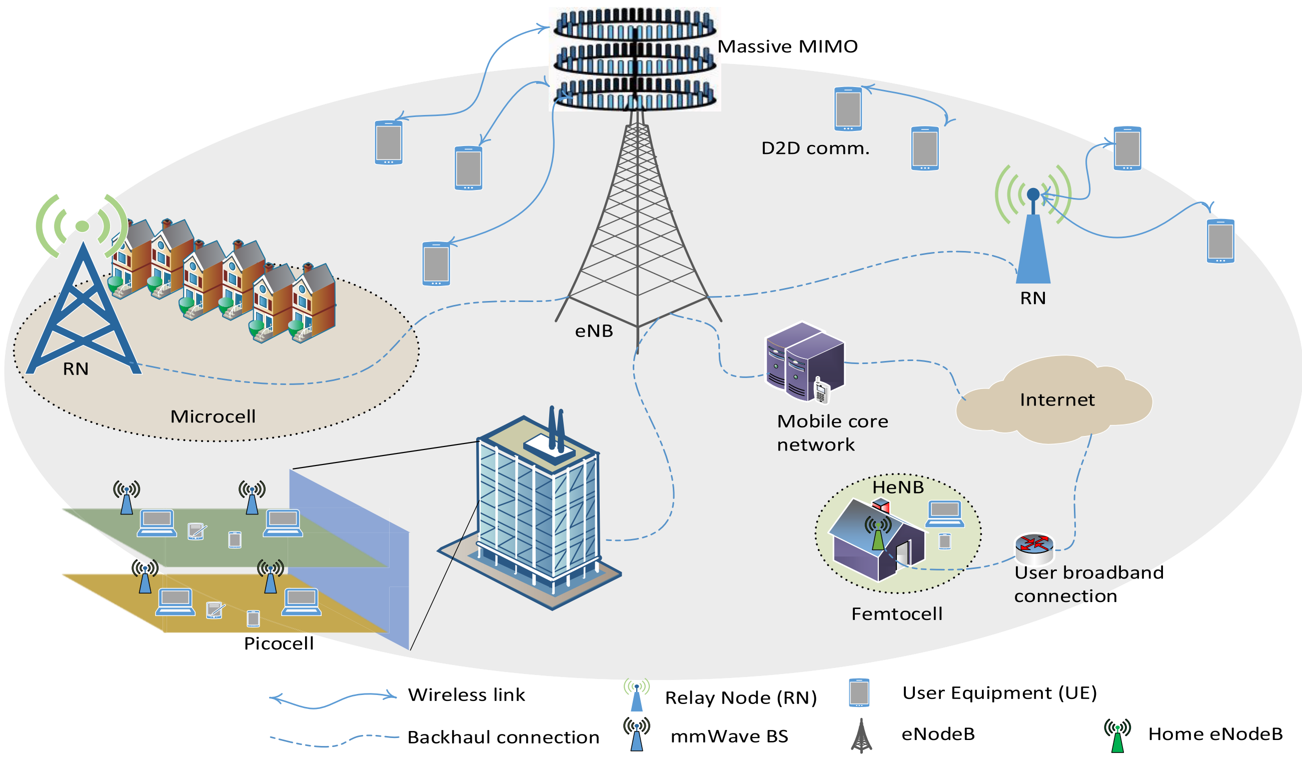

FIGURE 1. **Architecture of a multi-tier HetNet.**

the UDN environment and grouped the schemes based on six different UDN scenarios: an ultradense HetNet, an ultradense centralized Radio Access Network (RAN), ultradense D2D communications, massive IoT, massive MIMO and mmWave networks. Similar to [25], Kamel *et al.* [30] reviewed the issues concerning ultradense networks by examining nine key enablers of a UDN: resource management, scheduling, user association, backhaul networks, interference management, EE, spectrum sharing, propagation models and the cost of UDN deployment. Whereas [25], [30] focused on UDNs, a survey in [31] concentrated on RRM issues in machine-to-machine (M2M) communications. It mainly highlighted the techniques used for resource and power allocation, accessing unlicensed radio bands, RRM in the capillary network and ultradense HetNets. In [32], the authors focused on RRM in cognitive radio by organizing the techniques into the four steps of spectrum sharing: spectrum sensing, spectrum allocation, spectrum access and spectrum handoff. Other surveys that included RRM as a part of their study are presented in [33] and [34], which emphasized wireless scheduling strategies based on quality of experience (QoE) awareness and interference mitigation techniques in femtocell networks, respectively.

Compared to previous surveys, this study focuses on the RRM techniques for 5G HetNets, which will be different from the LTE/LTE-A HetNets. We categorize our RRM techniques based on the main focus of the resource allocation approach, such as the spectrum allocation and power allocation. These categories are also reviewed based on the different optimization metrics used for each technique. The justification for using varying optimization metrics as the subcategories is that services and applications in the 5G systems have set their priorities with different optimization metrics.

B. PAPER ORGANIZATION

In Section II, we begin our review with techniques that focus on spectrum allocation methods optimized for system throughput, SE, fairness, quality of service (QoS) and QoE. Then, we review the techniques used for the joint optimization of resource allocation and interference mitigation for both cross-tier and co-tier interferences. Next, RRM schemes that optimize joint resource and power allocation, maximize EE and apply energy harvesting methods are investigated. Joint resource allocation and user association methods are studied by considering backhaul limitation and load balancing issues. The complexities in implementing and computing RRM techniques are discussed with several possible schemes to reduce the complexities, and cloud RAN and multi-access edge computing (MEC) are discussed in the final subtopic section. The future scope of research is presented in Section III, and the study is concluded in Section IV. An outline of this study is illustrated in Fig. 2.

II. RADIO RESOURCE MANAGEMENT IN HETNETS

The recent trend of having mobile device connectivity anytime and anywhere has increased the demand for wireless communications services, resulting in the rapid deployment of wireless networks with different service capabilities.

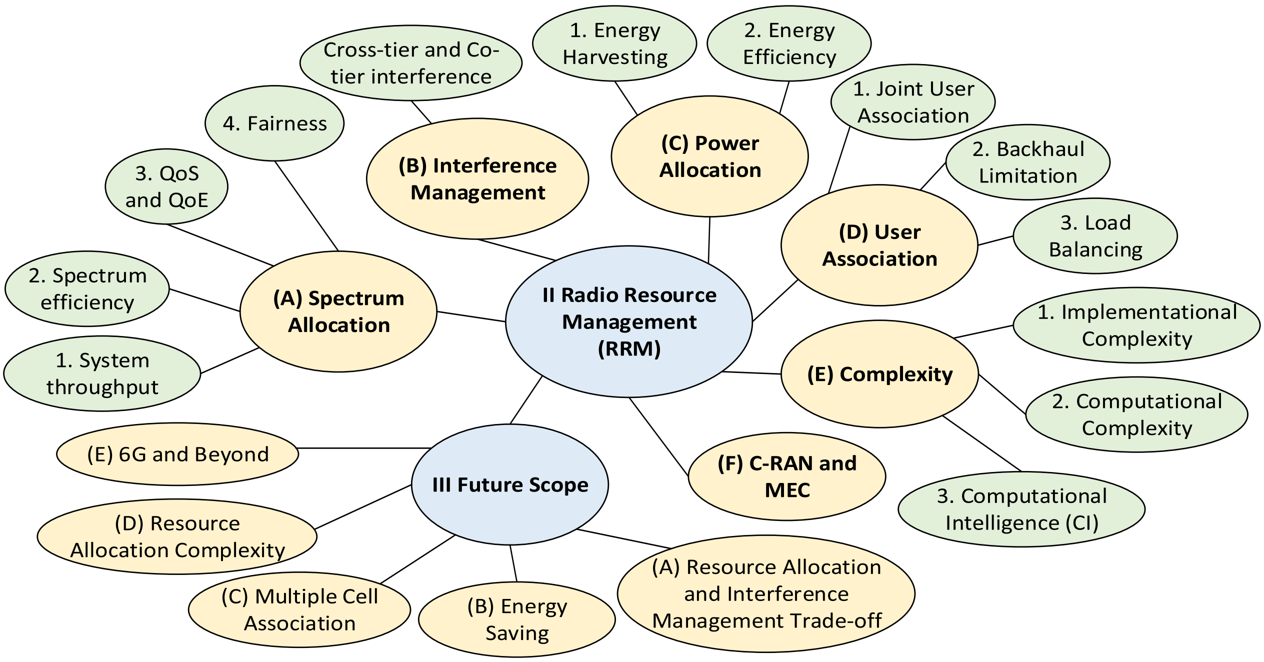

FIGURE 2. Outline of this survey.

The future of 5G systems concerns massive connectivity, between people through the cellular network and between equipment, machines, and vehicles using IoT, V2V and M2M features. To handle these demands, efficient radio resource management techniques are critical, especially in ultradense HetNets with multiple RATs. A widely used approach in radio resource management schemes is to implement flexible resource allocation that dynamically allocates available resources with different constraints, such as system throughput, energy awareness, or QoS awareness. We discuss the recent RRM techniques based on the mechanisms used in this section and subcategorize them using the optimization metrics considered in each technique.

A. RESOURCE ALLOCATION

Resource allocation is the process by which network resources are assigned to be used for wireless communications. Conventionally, resource allocation is designed to maximize the amount of successfully transmitted information to users in a network. However, traditional resource allocation will be unable to meet the demands for the vast amount of data required for various applications in wireless communications. The scarcity of the spectrum necessitates efficient radio resource management. Therefore, researchers have devised resource allocation techniques to optimize the performance metrics of the overall system, such as the system throughput, SE, fairness, QoS, and QoE. The next section discusses the current techniques for resource allocation based on the aforementioned optimization metrics. The works discussed in this section are summarized in Table 1.

1) SYSTEM THROUGHPUT

The system throughput is calculated as the sum of the data rate being sent successfully over all devices or terminals in a network and is measured in bits per second (bps) [35]. This section discusses the techniques used to maximize system throughput. In [36], the authors proposed a joint resource allocation with a user association method to maximize the overall network throughput using a Mamdani-type fuzzy logic controller (FLC). The users were first classified based on their data rate requirements, and the controller decided on the amount of bandwidth that should be allocated to each user depending on the available resources. The results were compared to greedy-based and best signal-to-interference noise ratio (SINR)-based approaches, and the results showed improvements in the data rate, bandwidth usage and blocking ratio. However, this work did not consider the network load balancing issue, which affects the overall system throughput. Another joint resource allocation method with user association and power allocation was proposed in [37] to solve the optimization problem, which was divided into two subproblems. The first subproblem was solved by fixing the power allocation, user association and resource allocation using graph theory via a Hungarian algorithm. For the second subproblem, the authors fixed the user association and resource allocation and solved the power allocation using the difference convex function approximation method. These two solutions were further simplified by using the modified Lagrange dual method to reduce their computational complexity. The results demonstrated that this technique can significantly improve the overall system throughput compared with the belief propagation algorithm [38], statistical

TABLE 1. Works on radio resource/spectrum allocation based on different performance metrics.

Performance Metric	Techniques	Advantages	Disadvantages	Ref.
System throughput	Lagrangian dual decomposition method	Fast convergence to the optimal value (a small number of iterations)	Co-tier interference is not considered	[41]
	-Centralized scheme: primal decomposition and cutting plane approach -Distributed scheme: Non-cooperative repeated game	The distributed scheme is more feasible in a large-scale network	SE decreases as the number of users increases	[39]
	-Power allocation: Stackelberg game -Sub-band allocation: OCF game	Extendable into more network settings	High system complexity	[40]
	Mamdani-type FLC	Improved system throughput compared to greedy-based and best SINR-based approaches	Network load imbalance	[36]
	-Graph theory -Difference Convex functions Approximation -Lagrange dual decomposition	A good trade-off between throughput and fairness	No service for UEs with bad channel condition	[37]
	-Lagrange dual decomposition -Iterative water-filling algorithm	Improved system sum rate	High computational complexity	[42]
	-Lagrangian dual decomposition -Newton-Raphson methods - Markov chain approximation	Multi-band access scheme performed better in a low-load condition	Load imbalance	[35]
	-Linear programming problem	Improved the EE, SE and system throughput	Not suitable for delay-sensitive applications	[43]
SE	-Regional Average Channel State -Maximum K-cutting in graph theory -Auction game model -Hybrid-Dsatur clustering algorithm	Improved frequency reuse and small cell throughput	No priority considered between SUEs and MUEs	[44]
SE + EE	-Cooperative spectrum leasing -Interference Alignment with Spectrum Leasing -Traffic Offloading with Spectrum Leasing	Extendable into more network settings	Cross-tier interference is not considered	[45]
	-PF allocation -Range expansion association -Stochastic optimization problem solved by the binary search algorithm	Fast algorithm, suitable for real-time implementations	High signaling overhead	[46]
QoS	-Nash Q-learning -Monte-Carlo tree search based Q-learning algorithm	Improved system throughput and system resource utilization while satisfying the QoS	High computational complexity	[51]
	-Markov queueing system	Reduced spectrum bandwidth usage compared to static resource allocation	High processing time	[52]
QoE	-Weighted bipartite graph and the revised Kuhn-Munkres algorithm -First-order derivative of the network utility	Performance increases with the increase of the cell radius	Resource allocation at the pico cell level only	[53]
Fairness	-Feedback-based method with PF -Lagrangian multiplier method	A good trade-off between throughput and fairness	Implementational complexity	[54]
	-Network flow optimization technique	Scalable with a number of users and network size	High signaling overhead	[55]

channel state information (SCSI), iterative water-filling and static full spectral reuse (SFSR). However, this scheme did not provide services for UEs with bad channel conditions.

Two types of joint resource allocation, centralized and distributed schemes, were proposed by Feng *et al.* [39], who combined resource allocation, user association and frame design in a wireless backhaul (WB) HetNet with MIMO. Their aim was to maximize the users' system throughput, constrained by both the fairness and the WB data rate. The centralized iterative scheme was decomposed into two subproblems: first, the user association was solved using a cutting plane approach; second, the joint frame design and resource allocation were solved by a primal decomposition approach. Both subproblems were iteratively solved until their convergence state to achieve an optimal solution. In addition, a distributed allocation scheme was also proposed by using repeated games between users, which was indicated to reach the Nash equilibrium. The results showed that the proposed method was robust to different network settings and achieved substantial improvement compared with heuristic and static pilot allocation schemes. Overall, the centralized scheme had better system throughput than a distributed scheme. However, the scheme incurred a large overhead, which makes its use unrealistic in a large-scale network. Additionally, the resources between WBs and SUEs are assigned orthogonally; hence, the SE decreases as the number of users increases.

Another implementation of a game theory approach was presented in [40], where a joint resource and power allocation method in a carrier aggregation enabled a HetNet. The authors proposed a framework based on a hierarchical game to optimize the transmit power and resource allocation of unlicensed users (UU) with the network operator's pricing strategies. The UUs' cooperative mode was modeled using a combination of overlapping coalition formation (OCF) and the Stackelberg game. The results showed that the power and resource allocation were stable, and its framework could be applied to a wide range of network settings with multiple BSs where the spectrum resources were shared cooperatively. However, the combination of OCF and Stackelberg games increased the complexity of the system, inducing a longer processing time Xu *et al.* [41] proposed a distributed resource allocation method for multiple users in a cognitive HetNet to maximize the system throughput while considering cross-tier interference and limiting the transmitting power of the small mmWave BS so that its effect on the macrocell network was tolerable. These small mmWave BSs were modeled as secondary users to detect the idle spectrum by the cooperative spectrum sensing method and access it using the underlay approach. The optimization problem was resolved using the Lagrange dual decomposition method, and the results showed that the algorithm could converge to its optimal value in a low number of iterations. Although the performance of macrocell users (MUEs) as the primary users is guaranteed in this method, this work did not consider co-tier interference, especially when the number of SBSs is high, which affects SBS users (SUEs).

A joint beam and power allocation in a mmWave small cell were proposed in [42] through formulation of the two problems into mixed integer nonlinear programming (MINLP). The nonconvex problem was broken into two subproblems, and the first problem was selecting the beam using cooperative games. Solving the first subproblem by obtaining an optimal beam allocation was crucial in determining the result of the second subproblem. In the second subproblem, the power allocation scheme was solved by the Lagrange duality and iterative water-filling algorithm. The results showed improvement in terms of the system sum rate but suffer from the high computational complexity of the optimal solution.

In [35], a joint user association and resource allocation problem in a multiband mmWave HetNet was proposed. Two cases: single-band and multi-band were considered for the UE transmission access type. For the single-band case, the joint problem was solved by determining the time fraction allocation then iteratively finding the optimal user association and power allocation based on the Lagrangian dual decomposition and Newton Raphson methods. For UE transmission using a multiband mmWave, the problem was solved using the Markov chain approximation method. The proposed work showed that UEs are most likely to transmit using the single-band scheme rather than the multiband scheme when the number of UEs is high. Although the multiband access scheme could provide better performance than single-band access, the results showed that better load balance and fairness can be achieved by UE transmission in a single band.

A joint routing and resource allocation scheme was proposed in [43] to maximize the EE in a mmWave network. This scheme considered an optimization for resource allocation in the link-physical layer and path selection in the network layer. For the first subproblem, the optimal solution for the resource allocation was obtained by using a stochastic algorithm. For the routing, the subproblem was formulated as a linear programming problem, and a linear programming solver was used to optimize the EE. The proposed scheme was able to improve the EE, SE and system throughput with an optimal routing selection. However, the cross-layer optimization might have induced delay and is not suitable for delay-sensitive UE.

2) SPECTRAL EFFICIENCY

The SE reflects the maximum amount of services to be derived from a given amount of spectrum and is measured in bits per second per hertz (b/s/Hz). Knowing this measurement can help MNOs decide how to effectively allocate spectrum and to whom. This section discusses the resource allocation methods that consider SE as one of the performance metrics.

With the aim of improving the SE, Ye *et al.* [44] proposed an allocation technique using the hybrid-clustering game algorithm while mitigating co-tier and cross-tier interferences. First, the clustering problem was solved using the maximum K-cut in graph theory based on the interference graph built by the influence of interference estimated by the regional average channel state (RACS) method. Then, the auction game mechanism was used to allocate resources for all users inside each cluster, where the cluster head was the primary user and other nodes were secondary users. By combining the clustering and auction methods, the algorithm confined the cross-tier and co-tier interference and instantaneously improved the SE. This method can successfully handle frequency reuse and low small-cell throughput issues. However, to eliminate both types of interference, small-cell users and macrocell users were treated on the same level in this work, which means that the priority and QoS were not considered.

While the authors in [44] only considered SE, the authors in [45] proposed an allocation scheme by aiming to improve both the spectrum and EE. They proposed a framework based on coalitional game theory to represent the cooperation of small cells, with spectrum leasing used as an incentive mechanism. Two resource management schemes were presented: Interference Alignment with Spectrum Leasing (IASL) by alleviating the co-tier interference using the interference alignment technique and Traffic Offloading with Spectrum Leasing (TOSL) for load balancing. The coalition of SBS in IASL was determined by the SBS themselves through comparison of the cost and revenue of the cooperation, followed by an MBS implementing spectrum leasing and power control. In TOSL, an MBS negotiates with the interfering SBSs to cooperate in the coalition and then offloads its corresponding MUEs to the agreed SBS. In return, the SBS is given a time slot in the MBS channel. These two schemes showed an improvement in their performance gains compared to the noncooperative schemes. Furthermore, the proposed framework can also be used in nonorthogonal multiple access (NOMA) and cognitive radio technologies. However, the interference alignment technique used can only mitigate co-tier interference, and this work did not consider the effect of cross-tier interference Xie *et al.* [46] proposed a resource allocation method that jointly maximizes both the area EE (AEE) and area SE (ASE). Their system model considered three schemes: (1) a range expansion association scheme to balance the load between the MBS and SBS, (2) fractional frequency reuse (FFR) to manage the inter-tier and intercell interference, and (3) proportional fairness (PF) allocation to guarantee fairness among users. To jointly maximize the AEE and ASE, the stochastic optimization problem was formulated and solved by the binary search algorithm. The proposed scheme was evaluated by using different settings for the power threshold, BS density, BS power consumption, and bandwidth partition for each cell, and the results showed that the ASE and AEE can be considerably improved with appropriate settings. The binary search algorithm in this method was confirmed to shorten the duration of finding the optimal value; hence, it is suitable in real situations. However, heavy signaling overhead is expected from this method due to its centralized approach in allocating resources by the MBS.

3) QOS AND QOE

For a wireless network to be considered to satisfy user requirements, its quality is measured as a collective effect of performance parameters related to the network, such as system throughput, end-to-end delay, and jitter and packet loss, which is known as the QoS [47]. Because 5G supports various services, there is an incentive for resource allocation to rely on QoS awareness [48], [49]. In addition to quality measured purely based on the network itself, the QoE has become another performance characteristic that reflects user satisfaction with the network [33], [50]. The QoS and QoE are presented in this section.

In [51], the authors proposed a strategy of accessing the RAT in a HetNet to maximize network throughput while assuring the QoS requirement by using a multiagent reinforcement learning technique. They divided the process into two sequential processes: RAT selection and resource allocation. For the RAT selection, the Nash Q-learning method was used to attain access strategies that can avoid collisions. The resource allocation problem was solved using the Monte Carlo Tree Search (MCTS)-based Q-learning algorithm. The algorithm searched for the best policy to maximize the system throughput by considering the QoS requirements. The performance was evaluated through comparison of the PF scheduling systems, LTE Assisted Algorithm and Online Learning Algorithm. The results showed that optimization could be achieved with a reasonable number of searches, and it outperformed other scheduling methods with regard to the system throughput and resource utilization. However, the algorithm had high computational complexity, as hundreds of iterations (for each search) were needed to converge and achieve the Nash equilibrium stage.

Whereas [51] aimed to guarantee the QoS as a whole, [52] focused on reducing the blocking probability of data services served by the macrocells and maximized the throughput of small cells. The authors presented a resource allocation approach that considered the network traffic in a control-data separation architecture (CDSA) HetNet to enhance the efficiency of resources in both the MBS and SBS. They proposed a conceptual hierarchy or resource allocation framework that consisted of 4 modules: 1) a classification module that identifies whether to be served by the MBS or SBS based on the communication characteristics, e.g., UE types, 2) a statistic module to manage the network's traffic and channel conditions, 3) an optimization module for resource allocation of available resources, and 4) a transmit module to establish transmission channels. The resource allocation problem was formulated by maximizing the throughput of data offloaded to the SBS (S-traffic) while ensuring that the resources for the MBS can satisfy the UEs served by the MBS (M-traffic). Three adaptive resource allocation schemes were proposed with different complexities: sequential search-based, bisection-based, and time-ordered schemes. Compared with the static resource allocation and the traffic-aware scheme, the results showed that the approach can save nearly

45.5% of the spectrum bandwidth. However, the number of iterations needed increased as the MBS traffic load increased; hence, it may cause higher processing time and the complexity will increase exponentially.

Wang *et al.* [53] proposed a joint resource and power allocation by using the QoE utility function in a HetNet with a macrocell and pico cell that used spectrum sharing in the underlay transmission mode. For the subcarrier allocation method, they constructed a weighted bipartite graph and revised Kuhn-Munkres algorithm to obtain perfect matching. For power allocation, the optimal power problem was solved by the first-order derivative of the network utility function. The results were compared with the average power allocation and PF algorithms and exhibited better performance. However, the resource allocation was only at the pico cell level and the QoE performance became worse upon increasing the cell size.

4) FAIRNESS

Fairness in wireless networks can be guaranteed by distributing a fair amount of resources (bandwidth) to each user according to their expected QoS from the network. It is important to consider fairness in the allocation schemes for 5G systems that demand more connectivity and services. This section discusses the research on resource allocation schemes that consider fairness as one of the optimization parameters.

The authors in [54], [55] considered the overall system throughput and fairness in their work, and both allocation methods were controlled in a centralized manner. In [54], the allocation method in a coordinated multipoint (CoMP)-enabled HetNet was performed based on the utility function, which used priority adjustment between the throughput and fairness using different utility function weights [56]. The proposed scheme utilized a feedback-based method to decide on the user's allocation and applied the PF scheme to obtain a balance between system throughput and fairness. Similar to [54], [55] proposed a resource allocation scheme that used the concept of weighted α-fairness based on a network flow optimization technique with a similar aim of balancing the performance in terms of the system throughput and fairness. First, the available bandwidth was divided fairly (e.g., UEs closer to the BS will get more bandwidth but will be limited by the highest modulation coding scheme available on that RAT) and added a dedicated weighting coefficient, α, to enable control of the throughput-fairness trade-off as a function of the UE's SE. This method enables resource management based on different traffic patterns, and it scales well with an increasing number of users and infrastructure nodes. However, these two works required high-complexity computations and implementation requires high signaling overhead.

B. INTERFERENCE MANAGEMENT

Signals transmitted from one device might interfere with other devices that communicate in the same or nearby frequency bands that are being used. In a multi-tier HetNet, two types of interference need to be managed properly: cross-tier and co-tier interferences. As the name implies, cross-tier interference refers to the interference occurring between users in different network tiers, such as between macrocells and femtocells, as shown in Fig. 3. Co-tier interference denotes the interference experienced by users within the same network tier. This section discusses the current research on interference management to mitigate both types of interference, which are summarized in Table 2.

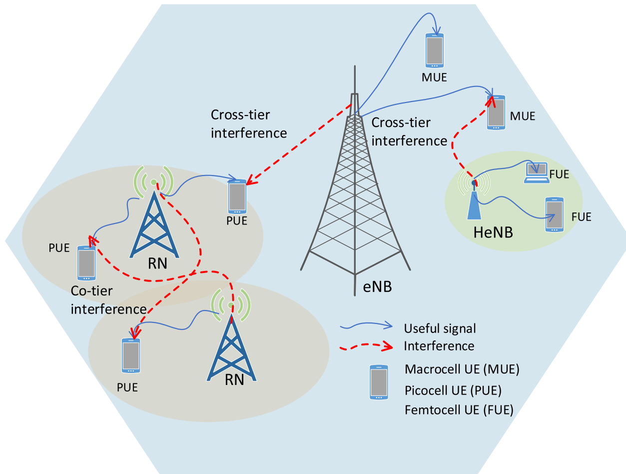

FIGURE 3. Interference scenarios in a HetNet.

Joint interference management with the resource allocation method was proposed in [57], in which the authors considered the HetNet as D2D-enabled, where tiers 1, 2, and 3 consisted of macrocells, small cells, and D2D pairs, respectively. The problem of joint sub-band and resource block (RB) allocation was solved as MINLP through consideration of the QoS requirements and power constraints. The joint sub-band assignment and resource block (RB) allocation were solved to maximize the D2D sum rate and minimize both co-tier and cross-tier interference. The FFR approach was applied for the allocation scheme and the D2D Downlink (DL)/Uplink (UL) decoupled (DUDe) scheme was proposed to alleviate both interferences. The work also proposed another method for the joint allocation problem, which was solved as a rectangular assignment problem. Although the scheme significantly alleviated co-tier and cross-tier interference compared to the traditional DL/UL coupled scheme, it had a time-consuming algorithm and took approximately 10 seconds to complete the allocation process for intracell orthogonal resource allocation; hence, the overall processing delay increased.

Research in [58] implemented an FFR method called FFR-3SL, which was a new FFR strategy that divided the resources into 3 sectors and 3 layers. The entire macrocell coverage area was sectorized into three sections and three layers, and the overall bandwidth was divided into seven sub-bands. Then, the sub-bands were distributed among femtocells and macrocells by employing the proposed algorithm. The scheme could manage the co-tier and cross-tier

TABLE 2. Works on interference management based on different performance metrics.

Performance Metric	Techniques	Advantages	Issues	Ref.
Co-tier + cross-tier interference	-Fractional Frequency Reuse -D2D DL/UL Decoupled scheme -Rectangular Assignment Problem	Better interference mitigation than the traditional coupled scheme	Time-consuming process	[57]
Co-tier + cross-tier interference	-3 sectors and 3 layers FFR	Higher throughput and capacity	High computational complexity	[58]
Co-tier + cross-tier interference + throughput	-Logarithmic function -K-means clustering	Eliminates interference by considering frequency reuse and fairness	Increased energy consumption	[59]
Cross-tier interference	-CSI overhearing -Normalized PF scheduling (PFS) -Iterative water-filling algorithm	No additional control overhead from MBS is needed; applicable to another type of channel quality-aware scheduler	Co-tier interference is not considered (among SUEs)	[60]
Cross-tier interference + throughput	-Geometric programming -Convex relaxation approach (logarithmic transformation)	QoS of MUEs is guaranteed	Unfair to the cell-edge users	[61]
Cross-tier interference + throughput	For MUEs: Improved simulated annealing algorithm -For SUEs: maximize minimum distance algorithm	Scheduling using MMD does not require global CSI	No service for low-SINR users	[62]
Minimum sub-band handoff frequency	-MAX-K cut problem -Network interference state map	Fast method, higher SE, and lower computational complexity than other frequency reuse schemes	Static resource allocation scheme	[63]
EE +QoS	-Finite horizon Markov decision process -Approximate dynamic programming	Adaptable to the QoS requirements	High computational overhead and processing time	[64]
System throughput	-non-linear optimization -Lagrange dual methods	Robust allocation scheme	High complexity	[65]
Maximum network-wide utility	-Dual decomposition method	Improves resource partitioning and load balancing gain	Shifts the complexity to end-user side	[66]

interferences, and higher throughput and better capacity were achieved. However, the allocation scheme imposed a high computational complexity due to its 3-layer and 3-sector structure.

Research in [58] implemented an FFR method called FFR-3SL, which was a new FFR strategy that divided the resources into 3 sectors and 3 layers. The entire macrocell coverage area was sectorized into three sections and three layers, and the overall bandwidth was divided into seven sub-bands. Then, the sub-bands were distributed among femtocells and macrocells by employing the proposed algorithm. The scheme could manage the co-tier and cross-tier interferences, and higher throughput and better capacity were achieved. However, the allocation scheme imposed a high computational complexity due to its 3-layer and 3-sector structure.

In [59], a resource allocation scheme was proposed for a three-layer HetNet, i.e., macrocell, pico cell, and femtocell, by considering cross-tier and co-tier interference. The scheme consisted of two stages, with the first stage for subchannel allocation and power control and the second stage for interference management. The first stage used the logarithmic function for the allocation by considering the minimum system capacity, power constraint and interference coordination. In the second stage, interference management was performed based on K-means clustering by dividing small cells into different clusters. This scheme has the advantage of eliminating the interference among various small power BSs in a fully distributed resource management manner. However, the energy consumption of the scheme was compromised due to the deployment of more pico BSs to enhance system throughput.

Another method that considered interference management as an optimization parameter was presented in [60], in which a distributed resource allocation method was proposed for the downlink of the MBS and SBS based on the Orthogonal Frequency Division Multiple Access (OFDMA). This work aimed to maximize the throughput of SUEs while alleviating interference with MUEs. Unlike conventional methods to mitigate interference caused by SBSs on MUEs that relied on the channel state information (CSI) provided by MBSs, this work proposed that SBSs predict the subchannels that were probably used by the nearby MUEs based on the locally overhead CSI. The SBS performs the resource allocation to its connected SUEs by using the estimated interference while considering the maximization of the data rate. The results demonstrated that the method efficiently mitigated the interference from SBSs to nearby MUEs and provided a trade-off between the MBS and SBS throughput. This work showed the advantage of a reduction in overhead signals and is applicable to other types of systems, such as cognitive radio. However, co-tier interference among secondary users was not considered in this work Xu *et al.* [61] proposed an allocation method that considered both the cross-tier interference and MBS transmit power constraints to allocate resources and improve the overall capacity. This allocation problem was solved by a semi-infinite programming problem, and the problem was then relaxed into geometric programming. The results showed that the algorithm can guarantee MUE and SUE performance under certain channel conditions, but the scheme's use of ultimate fairness can cause the same bandwidth to be allocated among users; hence, some users with bad channel qualities might not obtain services.

A multiobjective optimization method was used in [61] whereas the work in [62] proposed a scheduling method by applying a carrier aggregation approach with the aim of eliminating cross-tier interference. The scheme starts with categorizing the users into MUEs and SUEs, i.e., user association. This is followed by a cooperative transmission strategy that is SUE-centric to increase the data rate of SUEs. For cross-tier interference alleviations, an improved simulated annealing algorithm and maximize minimum distance (MMD) algorithm are used based on the location of SUEs and SBSs, respectively. The scheduling method using MMD does not require global CSI; hence, system overhead can be reduced. However, the fairness of the system was not considered; hence, users outside the radius and with a low SINR profile would not be served.

Niu *et al.* [63] proposed a fast resource allocation method in an ultradense HetNet, with the aim of alleviating the interference using the graph clustering algorithm. The scheme reduced the number of unnecessary sub-band hand-offs due to a new approach of allowing static UEs to stay in their allocated sub-band, provided their interference state satisfies certain conditions. To do this, an evaluation model for interference was defined in this work by using a new network interference state map (ISM) model. The results showed that the method provided a fast and efficient allocation method, with higher SE and lower computational complexity than other frequency reuse schemes. However, they considered a nondynamic resource allocation scheme that causes starvation for cell edge users Ayala-Romero *et al.* [64] proposed an interference coordination scheme with energy savings in a HetNet. They devised two problems as a finite horizon Markov decision process (MDP) by considering the traffic load and prediction of the network load to configure the network. They included the QoS requirements from the network operator as the constraint for the MDP formulation. The approximate dynamic programming algorithm was used for the MP by selecting the predicted energy-efficient configurations with guaranteed QoS. The ADP consisted of a certainty control principle to simplify the complexity of the MDP and a machine learning technique to predict the QoS and network load. The work was evaluated using an LTE-A network simulator, and the results showed an improvement in the QoS and energy-saving mechanism.

Similar to [64], Xu *et al.* [65] proposed a resource allocation scheme to maximize the system throughput by considering both cross-tier and co-tier interference for macrocell users and the transmission power in HetNet. The scheme was formulated through the use of a nonlinear optimization problem that was solved by distributed Lagrange dual methods. The results showed that the allocation scheme was robust enough and could confine the effects of channel uncertainties. However, the approach involved many iterations to converge to stability and hence might induce delays in the system.

Zhou *et al.* [66] proposed a resource partitioning method that can alleviate the interference caused by macro BS for offloaded users in a D2D enabled network. First, the user association problem was solved for load balancing by considering the network-wide utility maximization. The formulated scheme was based on the dual decomposition method, and the results showed that the scheme can provide gains in load balancing and resource partitioning. Nevertheless, this approach is not workable for the IoT or other devices that have power limitations since the complexity is transferred to the user side; hence, it loses its applicability.

C. POWER ALLOCATION

The transmit power control is a key criteria in 5G systems since future communications require green technology that consumes less energy. For these systems, the power allocation method must be considered to ensure that the EE is at the optimal level. In addition, varying the power according to user needs can also mitigate interference. This section discusses the optimization parameters that were considered in joint resource allocation with power allocation and are summarized in Table 3.

1) ENERGY HARVESTING

Lohani *et al.* [67] proposed energy- and interference-aware resource allocation with energy harvesting-enabled SBSs. The allocation was done by considering the channel state, type of activity, and amount of harvested energy. Whenever

TABLE 3. Works on power allocation based on different performance metrics.

Performance Metric	Techniques	Advantages	Issues	Ref.
Power consumption	-Q-learning -SoftMax decision-making and adoption of the logarithmic cooling technique	Reduced power consumption compared to the classical approach	Fairness is not considered	[70]
Power consumption + throughput	-Discrete binary PSO -Dual decomposition method -Dynamic programming -Greedy technique	An optimized trade-off between throughput and power consumption of SBS	High computational complexity	[67]
Power consumption + throughput	-Dual decomposition method -Sub-gradient method -Sub-optimal complexity greedy algorithm	Improved system throughput	High implementational complexity	[68]
EE	-Non-cooperative game -The dual Lagrangian decomposition method	Improved EE	Lack of interference management	[72]
EE + throughput	-Hungarian algorithm -Weighted-Tchebycheff -Dual decomposition method	Includes real blockage effects and environmental geometry	Fairness is not considered	[69]
EE + throughput	-Sum-rate maximization problem -First-order approximation based on an iterative algorithm	Fast convergence, improved throughput	Fairness is not considered	[71]
EE + throughput + SE	-Multi-objective optimization	NOMA-based, fast convergence, and controllable weight factor to consider both SE and EE	Trade-off between complexity and the number of SUEs served	[73]
EE + throughput + SE	-Joint power optimization (JPO) -Distributed power optimization (DPO)	Both methods (JPO and DPO) have better performance than CoMP-OMA	No substantial improvement in the EE	[74]
EE + throughput + fairness	-Optimal power allocation -Matching algorithm	SIC-stability concept (no equal power between users)	Single-cell network	[75]
System throughput	-KKT solved by the Alternate Optimization method	Can be extended to other channel model conditions, has fast convergence	Single-cell network	[76]

the harvested energy is low, most of the SBSs are switched off, which results in high power consumption in the MBS. However, if the harvested energy is high, lower power consumption in both the MBS and SBS can be achieved by activation of the SBSs. The proposed solutions were made based on the availability of future information. If future information is available, a dynamic programming-based and greedy algorithm is proposed. If the information is not available, it is solved in 2 iterative stages. The first stage determines the subchannel and power allocation for a given SBS using the dual-decomposition method. In the second stage, the SBS activation variables are determined using the discrete binary particle swarm optimization (PSO) technique. The numerical results showed that the offline solution performed better than the online solution. For the online solution, the dynamic programming technique performed better than the simple greedy algorithm but at the expense of high computational complexity.

2) ENERGY EFFICIENCY

Niknam *et al.* [68] proposed a centralized resource allocation method to maximize the overall throughput of a relay-based multiband HetNet by considering the power constraints and QoS of each user. This work allowed for users to switch between two air interfaces, i.e., licensed SBSs and an unlicensed SBS and MBS. The optimization problem was solved using the dual decomposition method, the joint resource allocation problem was solved by applying the subgradient method with the iterative algorithm, and a suboptimal complexity greedy solution was also presented. The proposed algorithm could overcome large path loss and shadowing at mmWave frequencies and achieved significantly high data rates. However, their centralized allocation method might cause high signaling overhead, increasing the implementation complexity.

A study in [69] proposed dynamic resource management by aiming to maximize the EE of cellular users while maintaining the QoS for D2D users. The BS decides on its strategy, either to maximize throughput or the EE, and the D2D users adjust their transmission power so that the QoS of cellular users is maintained. The authors solved the problems by dividing them into two subproblems: subcarrier allocation for D2D pairs and power allocation. The first subproblem was solved by using the Hungarian algorithm, which aimed to fulfill the minimum QoS and interference threshold for the cellular users. The second subproblem was to optimize both EE and throughput by formulating them as a multiobjective optimization problem, which was transformed into a single-objective optimization problem using the weighted-Tchebycheff method. An advantage of this method is that it included real blockage effects and environmental geometry, but fairness among users was not considered.

Similar to [57] and [69], [70] presented an allocation method for a D2D-enabled HetNet to determine the connectivity of a UE with the aim of minimizing the total transmission power while satisfying the bit rate requirements of different UEs. A UE can connect to one of the BSs available or to another UE (that acts as an access point) through out-of-band relaying D2D. The authors proposed a scheme based on Q-learning and soft-max decision-making in a distributive manner, where each UE makes a decision whether to transmit using BS or UE based on its own experience. This distributed approach has lower complexity than a centralized approach that addresses global optimization by jointly considering all BSs and UEs. The results showed that the performance was very close to the optimum. This approach successfully reduced the power consumption of the UEs compared with the traditional method of direct connectivity between UEs and BSs.

In contrast to the typical EE, a resource allocation scheme was proposed in [71] to maximize the weighted sum EE. The scheme permitted each BS to maintain different EE weight factors, and balanced the EE between the MBS and SBS. The problem was formulated as a nonlinear sum-of-ratios programming issue while guaranteeing the minimum data rate requirements of the users. However, the formulated problem was nonconvex; hence, a heuristic subchannel assignment algorithm was used to maximize the weighted sum EE. The power allocation problem was solved by parameterized transformations and a first-order approximation based on an iterative algorithm. The scheme showed a higher weighted sum of EE performance than the EE and SE maximization methods, and it took approximately 5 iterations for the algorithm to converge. However, the subchannel allocation might be unfair to some users (if the user's rate was not considered), e.g., if some users took almost all system resources while others had none.

A game theory approach was used in [72] to maximize the EE of a hybrid HetNet by combining a noncooperative game with the decomposition optimization method. The work divided the HetNet into outer and inner layers, with the different aims of maximizing the SUE data rate and EE, respectively. In the outer layer, the SBSs played a noncooperative game to determine the access policy and their operating frequency (either microwave or mmWave) until reaching the Nash equilibrium. The game can have an open access policy (by which it allows for MUEs to be connected to SBS by reducing interference at the cost of resources) or a closed access policy (by which it saves on resources at the expense of interference). In the inner layer, joint user association and power allocation were performed to maximize EE by using the dual Lagrangian decomposition method. The results showed promising performance improvement in the EE in a hybrid HetNet and could be enhanced further with a power control mechanism.

Whereas previous works presented power allocation in OFDMA-based HetNets, Zhang *et al.* [73] proposed a power allocation that considered the trade-off between SE and EE in a NOMA environment. They formulated the trade-off as a multiobjective optimization by setting the maximum transmit power and minimum QoS of the SUEs as constraints. The work provides a controllable weight factor to consider both the SE and EE according to network requirements using the weighted sum method. The results showed that the algorithms converged faster, and both the EE and SE performance were better than those of the regular orthogonal multiple access schemes. However, the number of SUEs that could be allocated in one subchannel was limited to maintain an acceptable implementational complexity of the Successive Interference Cancellation (SIC) at the receiver.

Another work based on NOMA was proposed to solve downlink power allocation by utilizing CoMP transmission in a two-tier HetNet [74]. The authors modeled a joint power optimization problem by maximizing the sum data rate of the CoMP-enabled BSs and dividing the scheme into three subproblems. The first subproblem was UE classification using CoMP or non-CoMP, which was done based on the received signal strength of the UEs. The second subproblem was to cluster the UEs using a low-complexity suboptimal user clustering method. The last subproblem was power allocation, which used the joint power optimization approach by solving the problem of sum rate maximization. The proposed joint method imposed a high computational complexity; hence, the authors solved the joint power optimization problem from derivations of the optimal power allocation for each BS in a distributed manner. The results showed a significant gain in the SE compared with the CoMP-OMA model, but there was no substantial improvement in the EE.

Zhu *et al.* [75] proposed a joint optimization of resource (channel assignment) and power allocation in a NOMA system by using the matching algorithm together with the optimal power allocation method. The work considered maximizing the max-min fairness (MMF), sum rate and EE with weights or the QoS as constraints for the performance criteria to determine the optimal power allocation, which was depicted in closed or semiclosed forms. The joint optimization was performed by fixing the channel assignment and optimizing the power. The optimization was performed alternately with fixed power allocation and was optimized for the channel assignment. This method provided optimal power allocation for all users over multiple channels at low complexity. The results showed better performance than those of the difference-of-convex programming and conventional-user-pairing methods. A new concept of the SIC stability was introduced in this work, which was important to prevent equal power allocation on each channel in the NOMA system to avoid large error propagation. However, this work only focused on a single-cell network.

A power allocation scheme was proposed in [76] to maximize the sum throughput of a NOMA system with α-fairness. Two categories of CSI were considered for use at the transmitter: SCSI and perfect CSI. For the first category, the power allocation was solved by maximizing the throughput with α-fairness by fixing the target data rate. For perfect CSI, the target data rates were adaptive according to the channel conditions, and the power allocation problem was solved by the alternate-optimization method. The results for both SCSI and perfect CSI showed considerable performance gains at the same level of fairness compared to OMA and fixed NOMA systems. However, this work only focused on a single-cell network.

D. USER ASSOCIATION

In HetNets, each user is associated with one of the available networks; to choose the best network for the user, a user association scheme is implemented. The association of the user is based on their demands, the distance from the BSs, and channel quality. User association is important to improve the SE, EE and load balancing of the network [77]. This section discusses the current work on joint resource allocation and user association schemes, and the studies are summarized in Table 4.

1) JOINT USER ASSOCIATION

The authors in [78] proposed a user association scheme to maximize the EE for a HetNet by nonlinear and mixed-integer optimization methods. They formulated the scheme as a three-layer iterative algorithm that starts with finding the EE parameter using the bisection method, followed by optimizing the user association index and transmit power. The user association and power allocation were solved by a dual decomposition and power update function. They provided a complexity analysis for the algorithm, which is proportional to the number of BSs, users, and number of iterations needed to reach a stabilized level.

In [79], the author proposed a joint resource allocation scheme with an optimal user association algorithm to minimize the network packet delay. He proposed three QoS-aware user association (QoSA) strategies: block-coordinate descent (QoSA-BCD), the alternating-direction method of multipliers (QoSA-ADMM), and multiflow (QoSA-MF). Compared with the conventional user association strategies, these algorithms minimized the packet delays at lower complexity in a distributed manner. However, co-tier and cross-tier interference was not considered and might cause problems in a multi-tier HetNet.

Similar to the work in [79], the authors in [80] suggested a QoS-aware strategy for their joint resource allocation and user association, with the aim of minimizing the overall power consumption. The authors solved the joint problem in two stages. In the first stage, the joint user association and resource allocation problems were solved using a cost-based algorithm. In the second stage, the power allocation problem was solved for each UE by considering the SINR and QoS in a distributive manner using the decomposition structure. The algorithm worked well in a large network and showed fast convergence behavior. However, each UE was only allowed to use only one unit of channel resource, and each MBS and SBS were not applicable to more than one unit; hence, fairness was not considered in this work.

Another work by Li *et al.* [81] proposed a joint user association and resource allocation scheme, and the two subproblems were solved using a nonlinear mixed-integer fractional programming method to maximize the EE. They considered the model in a multicast transmission scenario where the MBS was equipped with an Active Array System (AAS) and the SBS used omnidirectional antennas. The method was enhanced by considering the user's QoS by using the Dinkelbach approach and Lagrangian dual decomposition. The results showed that the proposed user association scheme had better EE performance than the max SINR user association algorithm. Furthermore, the convergence time for the algorithm was optimal with low computational complexity, which improves cost efficiency. However, when the number of users increased, the exhaustive search was no longer applicable. Whereas [81] considered AAS in a HetNet, Xu *et al.* [82] proposed an energy-aware user association in an energy-cooperated environment among the BSs. They were motivated by the trade-off between users offloading and energy cooperation. The user association scheme was based on the primal-dual interior-point method, and the results showed an increase in the EE for the energy-cooperation HetNet compared with that with no energy cooperation.

In [83], the authors proposed an energy optimization scheme for BS operation, user association, and resource and power allocation. The aim was to minimize the energy consumption without requiring traffic distributions by first solving the user association and resource allocation issues using closed-form solutions. This was followed by a fast and tuning-free algorithm to achieve optimal power allocation. The BS operation optimization was based on a greedy-style heuristic algorithm. The proposed approach showed a significant reduction in the energy consumption compared with existing schemes and was tunable according to power and delay trade-offs Chai *et al.* [84] proposed a joint user

TABLE 4. Research on user joint resource allocation and user association.

Performance Metric	Techniques	Advantages	Issues	Ref.
EE	Non-linear and mixed-integer optimization	Improved the load balancing, overall throughput, and EE	High power consumption with a low number of UEs	[78]
	Primal-dual interior-point method	Improved EE in energy cooperation environment	The decentralized decision is ignored	[82]
QoS + Optimal user association	-Block-coordinate descent (BCD) -Alternating Direction Method of Multipliers (ADMM) -Multi-flow (MF)	Low complexity	Co-tier and cross-tier interference are not considered	[79]
QoS Power consumption	-Cost-based approach -Relaxation and decomposition method -Distributed power update method	Fast convergence behavior on the large-scale network	Fairness is not considered	[80]
EE + QoS	Non-linear mixed-integer fractional programming method	Adopts multicast transmission services	When the number of users is high, exhaustive search is infeasible	[81]
Power consumption	-Closed-form optimization -Tuning-free algorithm -Greedy-style heuristic algorithm	Improved overall power consumption	Only considers transmitting power on data channels	[83]
Secrecy EE	- Kuhn-Munkres algorithm	Fast convergence for a HetNet	The complexity increases exponentially with the number of UEs	[84]
Network utility	-Mixed-integer nonlinear programming -Lagrangian dual method	Provided information on the effect of backhaul capacity on network utility	Co-tier and cross-tier interference are not considered	[85]
EE + CCI	-Machine learning-based game theory -Non-cooperative game solved by a distributed learning-based approach (DCA-LA) -Gibbs sampling method (GUIA) -No regret-based learning algorithm	DCA-LA algorithm is low-complexity	GUIA has higher complexity with a high convergence time	[86]

association and power allocation scheme in a secured DL HetNet. The problem was formulated as a multiobjective optimization by aiming to maximize the EE of BSs under the constraints of the BS power and minimum UE data rate. The optimization problem

was solved by applying the iterative method and Kuhn-Munkres algorithm. This work introduced the concept of secrecy EE, which is defined as the ratio of the transmission rate over a secured channel and the BS power consumption. The algorithm has fast convergence behavior over a HetNet, but its complexity increases exponentially when the UE association is below the target.

2) BACKHAUL LIMITATION

Backhaul limitation was chosen as the constraint in [85], and the authors proposed a resource allocation method to maximize the utility fairness for a massive MIMO-enabled HetNet. The optimization problem was solved as a mixed-integer nonlinear programming problem using the Lagrangian dual method. This scheme offered insight into the impact of the backhaul capacity on the network utility performance. However, the BSs, both macro and small BSs, were modeled to use the same frequency band, so they did not consider co-tier and cross-tier interference.

3) LOAD BALANCING

Another important aspect of multi-tier HetNets is the load balancing between the networks, as proposed by the authors of [86]. This paper proposed two dynamic channel allocation methods that were based on a learning algorithm (DCA-LA) and the Gibbs sampler technique, which considers the UE's interference (GUIA). The authors joined the two methods with a BS ON-OFF switching algorithm to lower power consumption. These methods aimed to improve the EE while considering co-channel interference (CCI) by joining the power and channel allocation. For resource allocation at the

TABLE 5. Research on computational and implementational complexities.

Complexity	Process	Overhead signal source/Time-consuming process	Advantages	Issues	Ref.
Implementational	Periodic channel estimation to obtain the average CSI	CSI	Adaptive to different network scenarios	Optimize time interval for uplink pilots	[39]
	MBS to decide on the user's resources	Type of services and users' weights	Subcarrier pairing that improves system sum rate	Type of services demanded by each user with their respective QoS	[68]
	Coordinating node decides on user association and radio resource utilization	Traffic demand and coverage probability	Balance between overall system throughput and fairness	Concentration of overhead signal is high	[55]
Computational	Overlapping coalition formation game	Negotiations of each UU with every SBS in the network	UU can transmit on multiple sub-bands	Time consumed to reach the equilibrium state increases with the number of relay BS	[40]
	Dynamic programming in 2 phases: planning and implementation	Generating the resource allocation lookup table (planning phase)	Greedy algorithm to reduce complexity	Complexity increases with the number of users	[67]
	Multi-agent reinforcement learning	Learning time	Options for traffic that is delay-sensitive and delay-tolerant	Trade-off between the learning time and optimal solution	[51]
	Markov queueing system based on the traffic congestion	Traffic-congestion calculation	Adaptive resource allocation schemes	Iterations increase as traffic load increases	[52]
	Data mining to study the complex traffic patterns	Learning algorithms to predict future traffic behavior	SON can be established	Processing time is long as a variety of traffic is involved	[99]

BS level, the DCA-LA strategy uses a game-theory approach where each BS learns its environment using the no-regret learning algorithm to select its channel and power level. For resource allocation at the UE level, the GUIA algorithm utilizes the information from its connected UEs to increase the network's performance and uses a Gibbs sampler to select the channels. These algorithms balance the load among BSs, improving the system throughput and SE. Nevertheless, the algorithms took a long time to converge to an equilibrium state, which could induce latency.

E. IMPLEMENTATIONAL AND COMPUTATIONAL COMPLEXITY

The complexity of future communication systems is expected to increase since they must satisfy many user demands such as higher data rates, massive connectivity, and very low latency. Fulfillment of these user requirements must provide seamless services and real-time response; hence, high latency cannot be tolerated. It is crucial to maintain the induced latency at a very minimum level (less than 1 ms) [14], [87], [88] and thus resource management techniques must address the implementational and computational complexities at the best possible level. The complexities of radio resource management are summarized in Table 5.

1) IMPLEMENTATIONAL COMPLEXITY

The amount of overhead signal and exchanged information between the BSs and users at every tier of the network makes RRM implementation in a HetNet complex. In resource management methods that use a centralized framework [39], [55], [68], the signal overhead can come from the network information such as the users' channel condition, and this becomes more critical in a larger network. For example, a centralized resource management approach based on the Dinkelbach procedure caused an increase in system complexity due to the large number of BSs and users in the UDN environment [89]. In [39], the overhead signal was generated from the channel estimation that was updated periodically to obtain the average CSI because it is impractical to use the instantaneous CSI due to the fast fading effect. Signal overhead can also come from the information on the type of services demanded by each user with their respective QoS, which are needed by the coordinating node to decide on the user's resources [68]. Furthermore, the concentration of the overhead signal is high when the entire heterogeneous system is controlled by a single coordinating node; users' traffic demands are collected and coverage probability information is used to decide which BSs the users are associated with and determine the number of radio resources that can be utilized [55].

Several methods can be used to reduce the implementational complexity via reduction of the overhead signal, including the clustering approach [90]–[92]. This was demonstrated in [63], where the communication overhead was reduced significantly using clustering, which led to a fast and efficient allocation scheme. Similar to [63], the work in [93] also used a clustering technique to minimize the overhead for the training signals by reusing the time slots among the BSs. Another method to reduce the overhead signal used CoMP transmission, as presented in [54], but it suffered an increase in latency due to its feedback-based method.

2) COMPUTATIONAL COMPLEXITY

Computational complexity refers to the processing time needed from acquiring the signal, deciding on the resource allocation, and transmitting the data back to the intended users. It reflects the computations involved in executing the resource allocation algorithms in a multi-tier HetNet. Computational complexity has become an issue in resource allocations as some algorithms yield a high number of computations that affect the processing time required, and might increase the hardware cost (higher cost for better performing machines). In allocation schemes that are based on game theory in [40], [42], [94], the time required to achieve a stable OCF game (Nash equilibrium) increases with the number of small BSs since each UU negotiates with every small BS in the network. A similarly high convergence time to reach its equilibrium state was reported in [86], where the resource and power allocation algorithms proposed are based on game theory and solved by machine learning. In future wireless communication, the usage of artificial intelligence (AI) techniques is an anticipated resource allocation approach as the RRM complexity increases [95].

In [36], a Mamdani-type FLC was used for the user association and resource allocation parameter, where the two inputs (user data rate and allocated bandwidth) were passed through the fuzzifier, inference engine and defuzzifier. Fuzzy logic provides an instant response to decide whether the user is associated with a certain SBS; hence, this solution is suitable for delay-sensitive services. In [51], [96], although the proposed reinforcement learning required a long processing time to reach its equilibrium state, the studies provided options for traffic that are delay-sensitive, delay-tolerant and power-sensitive. These options offer a smart way to determine the resource allocation method. The authors in [52], [67] used different optimization techniques to determine the resource allocation by the Markov queueing system, mixed MINLP and PSO. In [52], the authors proposed three schemes based on traffic congestion calculation methods and analyzed the schemes' complexity as the number of iterations needed to achieve stable results. The results show that the sequential search-based scheme took the most iterations to achieve stability since it is highly dependent on the traffic load (higher load, more iterations). This was followed by the bisection-based scheme that has a simpler searching method than the sequential search and time-ordered schemes, and used the last value of the allocated resource to reduce the number of iterations Lohani *et al.* [67] proposed an online approach to determine the resource allocation based on a dynamic programming algorithm. Although this method yielded a promising result in terms of throughput compared to an offline approach, it suffers from high computational complexity as it increases exponentially with users. Another interesting approach was presented by Calabrese *et al.* [97], where the RRM learning technique was split between the actors and learners. The learners learn the RRM policies from the collected data from actors in the network using a centralized learning framework. The actors execute the policies allotted by the learners in a distributed manner and generate samples of experience to be learned by the learners. One of the advantages of the split architecture is an improvement in the centralized learning framework, which can lead to an improvement for the whole RRM.

3) COMPUTATIONAL INTELLIGENCE (CI) TECHNIQUES

CI consists of three fundamental areas: neural networks (NN) that model the function of a 'brain', fuzzy systems that model the approximation of reasoning, and evolutionary computation that solves optimization. These three approaches usually work collectively to provide solutions to a wide range of applications with complex problems [98]. This section discusses the proposed CI techniques for resource management. A resource management technique combining a hybrid clustering method and game theory was proposed in [44]. Optimal clustering was performed using maximum K-cutting in graph theory and an auction game between a single auctioneer and multiple bidders to allocate the radio resources. This approach takes full advantage of clustering to minimize the overhead signals and uses an auction mechanism to improve the SE, improving the overall performance. In addition, a recent clustering technique was proposed in [99], which uses data mining to study the complex traffic patterns and cluster them according to cell behavior. Various machine learning algorithms can be used to predict future traffic behavior to establish the self-organizing network (SON).

Three resource management schemes are proposed in recent works by Munir *et al.* [100] using CI techniques for different 5G mmWave HetNets. These schemes combine the optimization method and game theory to reduce the overall complexity and overhead signal. The first scheme was for single-mode microwave networks, and two noncooperative games are played sequentially [101]. In the first game, the SBSs decide on the access policy to connect MUEs through an open, closed or hybrid policy. The objective is to maximize the SUE data rate using a greedy algorithm. The second game is played by the MUEs to re-evaluate the MUE connection to SBS (if the QoS is satisfied) and finalize other unconnected MUEs. The aim of the second game is to maximize the MUE data rate without affecting the system. The results showed that the scheme was user-centric, and the sum rate increased as the number of SBSs increased. The second scheme in this work incorporated single-mode hybrid networks (microwave and mmWave) modeled as a two-layer framework. The outer layer played a noncooperative game to decide on the SBS access policy to connect the MUEs and select the operating frequency. After the game achieved Nash equilibrium, joint MUE association and power allocation were performed using the dual Lagrangian decomposition optimization method. The last scheme in this paper used a dual-mode hybrid network, which was designed as a one-to-many matching game. The SBSs can operate in both microwave and mmWave frequency bands whereas the MBS only operates in the microwave band. At each SBS, resource allocation in the mmWave band was done by SUEs and mmWave subcarriers playing the game with the utility function as the data rate. In the microwave band, the game players are the connected MUEs and microwave subcarriers with the EE as the utility function. At the MBS, the allocation was the same as for the SBS for the microwave band. The results for the three schemes showed that a hybrid network with dual-mode SBS was the best candidate for a 5G HetNet.

F. CLOUD RAN AND MULTI-ACCESS EDGE COMPUTING

To fulfill the ultralow latency and high mobility requirements of a 5G system, multiaccess edge computing (MEC) technology may mitigate the computational load by the UE, especially in regard to user applications that require intensive computation. It can process a high volume of data prior to sending it to the cloud within the RAN closer to the UEs. The co-deployment of MEC and cloud-RAN (C-RAN) technology takes advantage of network function virtualization (NFV) and is beneficial in terms of cost and scalability from the mobile network operator's (MNO) point of view [102] but it requires overcoming some technical challenges such as network management, especially in HetNets.

A MEC-enabled C-RAN in a UDN was proposed in [103] to optimize the EE by joint task offloading and resource allocation. The optimization was formulated as a stochastic MINLP problem and, based on the Lyapunov optimization theory, the problem was solved by a dual decomposition method and matching game. The results showed a reduction of more than 50% in the energy consumption and average delay compared with the random offloading scheme.

Whereas [103] focused on MEC in C-RAN, Yang *et al.* [104] focused on a heterogeneous MEC with multiple servers cooperating by using blockchain as the security mechanism. The combination of blockchain and heterogeneous MEC was implemented with a bloom filter as the carrier for routing. The proposed architecture was tested under an experimental setup with multiple MEC servers (in virtual machines) and a Hyperledger-based blockchain network, and the results showed a reduction in the privacy exposure of the MEC system. In addition, the MEC collaborations were more efficient and adaptive to network changes.

For C-RAN, the traditional C-RAN is no longer able to accommodate the high volume of users, and the connections among Remote Radio Heads (RRHs) and Baseband Units (BBUs) have become more complex to meet user requirements. Due to the substantial communications between RRHs and BBUs, elastic optical fiber switching and networking are imposed, corresponding to higher transfer speed, low cost, and transparent multirate traffic transmission, which cannot be achieved by traditional C-RAN architecture. Therefore, the authors in [105] presented a novel C-RAN over optical fiber (C-RoFN) architecture for multiple strata of radio resources, both optical and BBU, by software-defined networking (SDN). The proposed architecture was demonstrated experimentally using a testbed SDN with OpenFlow-based enhancement. The results showed that this strategy was successfully utilized across radio frequency, elastic optical network, and BBU resources to maximize radio coverage with reduced service delay. A similar experimental setup on C-RoFN was reported in [106] with multidimensional resource integration that focused on service provisioning by introducing a scheme based on the auxiliary graph. The experiment using the same testbed showed an increase in efficiency compared with other provisioning schemes in terms of the resource utilization, path blocking probability, network cost, and provisioning latency.

III. FUTURE SCOPE OF RADIO RESOURCE MANAGEMENT

In this section, we discuss prospective research topics for future wireless communication networks.

A. RESOURCE ALLOCATION AND INTERFERENCE MANAGEMENT TRADE-OFF

The effectiveness of cross-tier and co-tier interference mitigation techniques is crucial to guarantee the overall performance of HetNets. To date, interference mitigation remains a challenging task in resource management, as it must concurrently maintain the system throughput, spectra and EE, as well as maintain an acceptable level of complexity. This will become an interesting research area in which the trade-off between interference suppression and radio resource allocation can be analyzed. Future users have different needs for a variety of applications; thus, it is imperative to determine suitable policies on accessibility and the effect of radio resources and interference management in multi-tier HetNets. Another interesting problem to consider in interference mitigation techniques is reducing the number of overhead signals that contain CSI to reduce the number of information exchanges between MBSs and SBSs.

B. ENERGY SAVINGS

Energy consumption in a network will determine the cost for operators to set up the network. Hence, it is important to handle the EE of a network at the optimal level to satisfy a user's QoS and QoE. The power consumption of the overall HetNet can be reduced by using renewable energy sources for both MBSs and SBSs, and 5G is expected to employ more 'green' technology. Both MBSs and SBSs should be able to harvest their own energy from the environment. Another area of interest is exploring cooperation between BSs to create a more energy-efficient network.

C. MULTIPLE CELL ASSOCIATION

User association schemes in HetNets highly depend on the load balancing of the network, optimization metrics, network distribution, and traffic models used. Multicell user association is an emerging scheme in which users can be connected to multiple SBSs to achieve higher data rates and SE. Therefore, it would be interesting to see more research on multicell association schemes. Another noteworthy research area is the classification of users before they are associated with the MBS or SBS to improve the effectiveness of user association. In addition, there is room for improvement in user association schemes by considering joint optimization with other features such as interference mitigation, fairness, and load distribution.

D. RESOURCE ALLOCATION COMPLEXITY

The implementational and computational complexity of resource allocation must be carefully handled to distribute resources efficiently and to be conducive for implementation. However, most of the schemes induce high computational and implementational complexity, which results in longer processing time and indirectly increases the deployment cost. Therefore, more prudent schemes with lower complexity and fast algorithms are needed to avoid adversely affecting the overall performance. Although these schemes can successfully reduce the complexity and processing time, the complexity of the algorithm was not measured. Hence, an interesting future research area is the measurement of the algorithm complexity to determine the feasibility of implementing such schemes. Another topic of research interest is the techniques used to reduce the overhead signals (the major contributor to the network's implementational complexity), such as joint resource allocation with clustering and CoMP-enabled HetNets. Prospective radio resource management may employ computational intelligence techniques to reduce the computational complexity and overhead associated with future 5G HetNets.

E. 6G AND BEYOND

Future mobile and wireless communications will utilize mmWave systems instead of existing UHF networks, which have different propagation characteristics. The 6G networks and beyond will utilize mmWave (30 GHz to 300 GHz) and Tera Hz (300 GHz to 3 THz) signals due to large portions of accessible spectra for applications that require very high data rates at 100 Gbps or higher. However, to utilize these frequency regions, a paradigm shift in managing these systems is needed since the characteristics of these signals are very different from those of traditional UHF signals. Physically, the atmospheric attenuation at these frequencies is very high, particularly for frequencies above 800 GHz. However, this can be compensated for by highly directional antennas and extremely narrow beams. It is possible to achieve secure communications and prevent eavesdropping on transmissions. Nevertheless, more research on the security of THz signals is needed in the physical-layer and transceiver designs that will comprise an anti-eavesdropping element. For THz signal modulation, new schemes that can provide at least 14 bits/s/Hz spectral efficiency are crucial to achieving very high data rate requirements. However, this is not viable using existing modulation techniques; hence, more work is needed in this area. For hardware, future transceivers that can operate at the THz range are major challenge for the industry, and there is ongoing research on power amplifiers with a frequency threshold of 500 - 750 GHz. However, changes in antenna designs are required to incorporate substantially dense antenna arrays considering these extremely short wavelengths. For the EE of the future 6G networks and beyond, a system that operates in mmWave and THz frequencies is more energy efficient than the sub-6 GHz networks. This is supported by the consumption factor theory (CF), which provides a metric for power trade-off for a communication system. For the spectrum usage strategy, regulatory bodies such as ETSI and ITU are working on the THz spectrum strategy to make it sustainable in the far future. This spectrum strategy is also vital to prevent new systems operating in the THz spectrum from interfering with existing space-based communication systems such as satellites. Finally, the impacts on human health due to radiation from THz transmissions should also be carefully studied since more applications using THz signals will be available in the future.

IV. CONCLUSION

The imminent 5G system will accommodate a wide range of devices and applications, which will increase the demands for higher data rates and almost zero latency. Applications such as the IoT, Internet of Vehicles (IoV) and smart electrical grids are expected to be supported by 5G. To accommodate these applications, allocations of radio resources must be carried out effectively and economically. In this study, recent radio resource management issues in HetNets were reviewed, including interference mitigation, spectrum allocation, power allocation, user association, complexity, and future research topics. The review began with an overview of HetNets, which have become the essence of future wireless communication networks, followed by recent works on the techniques of allocating radio resources (spectrum allocation) in HetNets. With multi-tier networks, interference management has become a crucial problem that requires special attention as it is closely related to the fulfillment of user requirements. Recent works on power allocation methods, which is important in realizing green technology in wireless communications, were reviewed. Several user association schemes that are important to achieve the optimal operation of a HetNet were described. After reviewing the techniques, an analysis of the complexity of resource management in terms of implementation and computation was provided. Then, works on C-RAN and MEC were reviewed. Last, this paper proposed the scope of study for radio resource management that will be beneficial for future researchers to explore.

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