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RESEARCH ARTICLE

User Association and Load Balancing Based on Monte Carlo Tree Search

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ABSTRACT The user association algorithm for 5G ultra-dense heterogeneous networks (UD-HetNets) comprising multi-tier base stations is becoming increasingly complex. In UD-HetNets, small base stations (SBSs) play an important role in offloading data traffic of user equipments (UEs) requiring high data rate from macro base stations (MBSs) to enhance the quality of services (QoS) of them. However, the traditional cell range expansion (CRE) scheme poses a risk of congestion in certain SBSs and the emergence of UEs monopolizing resources in less congested SBSs, which causes SBS load imbalance and decreases fairness performance. At the same time, determining the optimal user association result for load balancing, considering all possible combinations of associations between UEs and SBSs, leads to prohibitively high computational complexity. To obtain a near-optimal user association solution with manageable computational complexity, in this paper, we propose a heuristic algorithm based on Monte Carlo tree search (MCTS) for user association in UD-HetNet. We model the user association problem as a combinatorial optimization problem and provide a detailed design of the MCTS steps to solve this NP-hard problem. The MCTS algorithm obtains a near-optimal UEs-SBSs combination in terms of load balancing and maximizes the fairness of the overall network. This combination derived from the proposed algorithm aims to achieve load balancing among SBSs and mitigate resource monopolization among UEs. The simulation results show that the proposed algorithm outperforms conventional user association schemes in terms of fairness. As a result, compared to traditional CRE schemes, the proposed method can provide good performance to the UEs receiving data rates of the bottom 50%. Furthermore, the gap between optimal and heuristic solutions does not exceed 4%. Due to its manageable computational complexity, the proposed algorithm can be implemented as an xApp on the O-RAN near-real-time RAN intelligent controller (RIC).

INDEX TERMS User association, ultra-dense heterogeneous network, load balancing, Monte Carlo tree search, cell range expansion.

I. INTRODUCTION

In the 5G era, the ultra-dense heterogeneous network (UD-HetNet) architecture is in the spotlight as an essential technology for increasing mobile network capacity by densely deploying multiple small cell base stations (SBSs) in a macrocell [1], [2], [3]. The density of user equipment (UE) and volume of mobile traffic are extremely high in hotspot areas [4]. The network capacity and spectral efficiency can be dramatically improved through the densification of mobile networks, and the UD-HetNet can accommodate the explosive increase in mobile traffic. However, UD-HetNets

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make the user association problem much more complex than homogeneous networks [5].

User association is important for achieving load balancing and improving the spectral efficiency of 5G networks [6]. Because of the high density of base stations (BSs) and UEs in UD-HetNets, the number of UEs-BSs association combinations becomes extremely large, and the computational complexity increases significantly. For example, for N BSs and M UEs, the number of possible combinations is N^M. Among these combinations, the network must determine the optimal association result that maximizes the overall network capacity using a new user association algorithm with reasonable computational complexity.

In homogeneous networks, the max-RSS (received signal strength) user association algorithm, where the UE associates with the BS providing maximum received power, is widely used [7]. However, this algorithm leads to a strong load imbalance in the HetNet due to the transmit power disparity between the macro base station (MBS) and SBS [8]. In the max-RSS user association, the UE may not select the SBS, although many other UEs are already associated with the MBS because the transmit power of the MBS is much larger than that of the SBS. The user's data rate is determined by the serving BS's received power and load [9]. Because max-RSS does not consider the load of the BS, the UEs experience poor data rates, and the overall network capacity is degraded. Therefore, the UEs must be distributed to the proper SBSs to achieve load balancing and maximize the network capacity.

To manage load imbalance, a biased received power-based user association algorithm has been proposed [10], [11], [12]. This association scheme expands the range of SBSs and enables the offloading of UEs from MBSs to SBSs. This algorithm is called cell range expansion (CRE), which is an effective scheme for tractable network models with uniformly distributed UEs [9].

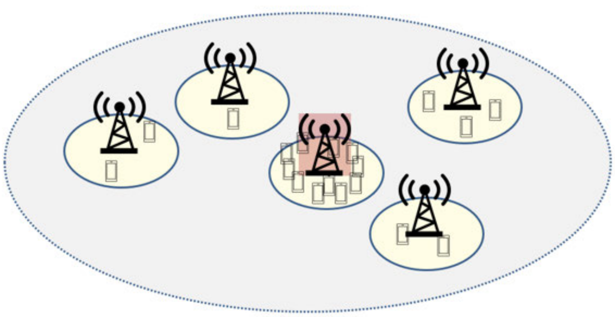


FIGURE 1. Load imbalance between SBSs.

In the CRE scheme, the UEs are offloaded to the SBSs, serving the highest biased received power. However, applying CRE in the practical network environment with non-uniformly distributed UEs will overload some SBSs and result in severe load imbalance, as shown in Fig. 1. CRE results in UEs-SBSs combinations where some UEs are consuming excessive resources while others are experiencing resource scarcity. In other words, CRE can pose a risk of load imbalance with congestion in certain SBSs while also leading to the emergence of UEs monopolizing resources in less congested SBSs. As a result, the data rates of UEs in congested SBSs are severely degraded. To address this load imbalance problem, we propose a sophisticated user association scheme that aims to distribute these UEs to neighboring SBSs with lower biased received power but smaller loads. We present a heuristic approach to increase the data rates of UEs in congested SBSs while concurrently reducing the data rates of UEs monopolizing resources within resource-constrained SBS networks. A heuristic algorithm can efficiently handle the real-time changing and dynamic channel status of 5G SBS networks [13]. This will improve the load fairness among the SBSs and the quality of services (QoS) for UEs in a dynamic wireless network.

A. RELATED WORK AND OUR APPROACH

In recent years, many studies have suggested user association algorithms for load balancing in 5G networks. A millimeter wave (mmWave) user association scheme that achieves load balancing in the reconfigurable intelligent surface (RIS) networks with multi-player multi-armed bandit is proposed in [14]. In [15], a traffic prediction-based load-aware user association scheme to maximize the utility function of the load balancing index has been suggested. The authors in [16] formulated a multi-objective optimization problem for load balancing while tackling the blockage problem in mmWave networks. However, the computational complexity of the schemes in [15], and [16] makes their practical implementation challenging and less feasible for real-time operation in dynamic network environments [5]. Furthermore, the solutions obtained may be suboptimal or even inaccurate by solving the dual problem instead of the primal problem and relaxing the combinatorial constraint. In addition, [17] proposed a deep reinforcement learning-based distributed algorithm for load balancing utilizing local information with a simple static network environment and a limited number of UEs.

This paper aims to introduce a novel, centralized user association strategy for efficient offloading and load balancing with reasonable computational complexity. The future networks are envisioned to be configured based on the O-RAN architecture, in which the radio access network (RAN) intelligent controller (RIC) manages multiple BSs and UEs [18]. The centralized approach is suitable in the O-RAN architecture because the RIC has all the information about the networks it manages [19]. Centralized schemes exhibit superior performance compared to other schemes, such as distributed and hybrid schemes, but they have high computational complexity [20]. To overcome the high computational complexity of centralized schemes, the proposed algorithm is based on Monte Carlo tree search (MCTS). MCTS is a heuristic tree search method for determining a near-optimal solution by repeating random sampling several times instead of exploring all cases [21]. Therefore, the user association algorithm based on MCTS can achieve near-optimal association results in terms of load balancing with a lower computational overhead. This result represents the near-optimal UEs-SBSs combination, ensuring that each UE is associated with the most suitable SBS. This approach increases load fairness and improves the data rates for UEs suffering from severe load imbalance. In other words, unlike the one-shot algorithms (e.g., CRE), the MCTS-based scheme employs a sophisticated approach to achieve load balancing among SBSs with reasonable complexity.

The authors of [22] proposed a distributed radio access scheme using MCTS. They divided this scheme into two processes: user association and resource allocation. The MCTS was used for resource allocation and not for user association. During resource allocation, each UE employed MCTS-based Q-learning to search for an optimal scheduling strategy. However, while the MCTS operation is supportable by the central entity, it is a significant computational burden for the UEs, which have a limited energy budget. In addition, as UEs find their optimal strategy using the MCTS, each UE becomes more selfish and does not consider fairness within the overall system. Furthermore, the number of UEs in the simulation was very small (less than eight). Efficient user association algorithms should be applicable to places with many UEs (e.g., hotspot areas). In places with few UEs, each UE can obtain a data rate above a certain level without a sophisticated scheme. In our algorithm, the centralized RIC employs MCTS to formulate the entire user association problem in detail, considering the fairness of the overall network. We present the simulation results for hundreds of UEs in Section IV, demonstrating that our algorithm can be applied to numerous UEs.

B. CONTRIBUTIONS

The major contributions of this paper are summarized as follows:

- We define a combinatorial optimization problem to model a user association problem and design an MCTS-based algorithm to solve this NP-hard problem without any modifications of objective function or relaxation of constraint while maintaining reasonable computational complexity. We can optimize user association for numerous UEs by leveraging RIC with sufficient computing capabilities. Furthermore, with a slight modification, the MCTS-based algorithm can effectively solve other binary programming problems in the field of mobile communication, e.g., admission control in network slicing [23].
- To the best of our knowledge, this is the first manuscript on user association and load balancing based on the MCTS framework. Since achieving data rates above a certain threshold does not significantly increase user satisfaction, the proposed algorithm distributes the resources of UEs that have been allocated too many radio resources to UEs with significantly lower data rates through SBS load balancing.
- We consider a realistic network scenario where multiple UEs with different service requirements coexist. In fact, UEs that demand low data rates (e.g., voice call, SMS) only need to maintain network connectivity and thus may not require sophisticated user association algorithms. The MCTS-based user association algorithm is selectively applied to UEs that require high data rate services, such as file transfer protocol (FTP) and video streaming (hereafter abbreviated as HDR UEs). RIC detects the HDR UEs in the network and offloads them to SBSs. First, using the max-RSS algorithm, all UEs are associated with the macrocell as an anchor cell. Consequently, UEs requiring low data rate services maintain their connection with the macrocell, while UEs requiring high data rate services (i.e., HDR UEs) are offloaded to SBSs. The proposed user association algorithm is employed for the offloading process.

The remainder of this paper is organized as follows. Section II presents the system model of UD-HetNet, including network architecture and optimization problem formulation. In Section III, an MCTS-based user association algorithm is proposed. The performance of the proposed algorithm is evaluated in Section IV using simulation results, and the conclusions are presented in Section V.

II. SYSTEM MODEL

A. NETWORK ARCHITECTURE BASED ON O-RAN

In order to implement the UD-HetNet in practice, we adopt the O-RAN architecture proposed by the O-RAN Alliance [24]. Standardized open interfaces enable the interoperability of RAN elements from different vendors, reducing capital expenditures and making the O-RAN architecture a suitable model for UD-HetNets with numerous SBSs. For example, the radio units (RUs) from vendor A are interoperable with the distributed units (DUs) produced by vendor B. To minimize the cost of deployment, a network operator's SBS networks are expected to be composed of equipment from various vendors. Traditionally, the lack of standardized specifications for gathering information from equipment produced by different vendors made it difficult to deploy an authorized controller to monitor the overall network status [25]. Thanks to the open interfaces of the O-RAN architecture, operators can utilize the RIC to gather information from SBSs created by different vendors (Fig. 2). The RIC can assess the SBS network's status and derive the optimal user association results from the gathered information, achieving load balancing.

The additional technologies of the O-RAN architecture that enable efficient control and scalable management of UD-HetNet include virtualization and intelligence. As shown in Fig. 3, the system model for evaluating the performance of the proposed algorithm in O-RAN-based UD-HetNet is developed. The management functions in RIC can be implemented as virtual network functions (VNFs) [26].

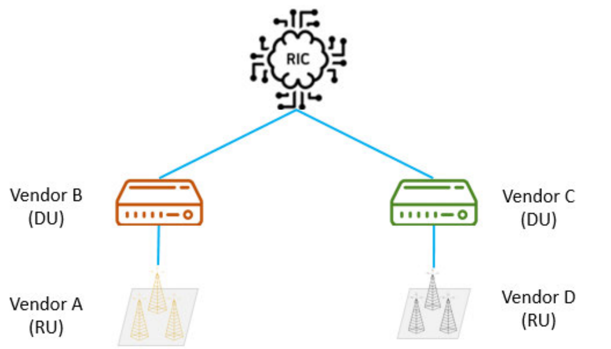


FIGURE 2. An SBS network consists of equipment from different vendors controlled by RIC and open interfaces.

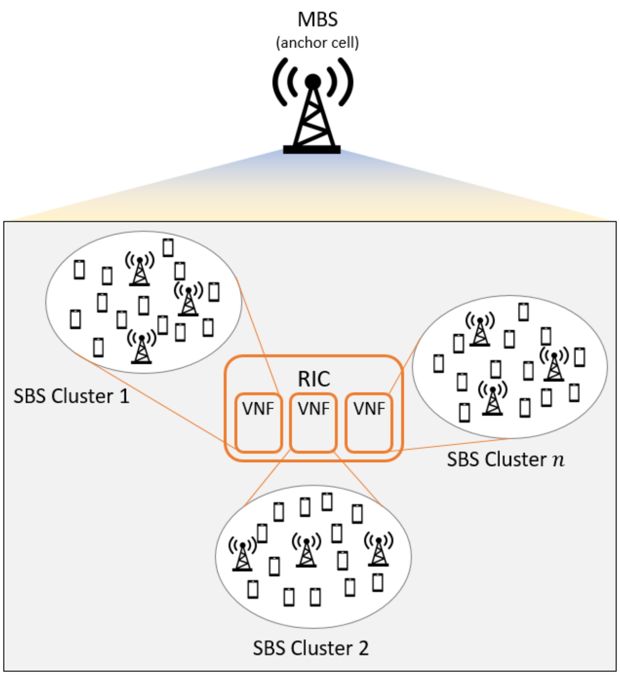


FIGURE 3. System model with RIC and SBS clusters.

Thanks to the scalability and flexibility of VNFs, one RIC can efficiently control multiple SBS networks. The RIC can isolate computing resources that manage different SBS networks and dynamically adjust the allocation of resources according to the network situation. The proposed heuristic algorithm can be applied independently to each SBS network. Considering that the computational complexity and execution time of the algorithm depend on the number of UEs and SBSs, the RIC can appropriately cluster the number of SBSs and UEs within one SBS network. The MBSs are assumed to function as anchor cells for basic communication, such as voice and SMS. In contrast, SBSs are used as capacity boosters that serve HDR UEs using services like FTP, video streaming, and so on. The percentage of HDR UEs is assumed to be 30%, which means that the proposed user association algorithm is applied to 30% of UEs [27].

The RIC contains multiple VNF components to serve intelligent services for SBSs and UEs. Specifically, the RIC has monitoring/logging systems, databases, and software applications for managing mobile networks. O-RAN Alliance defines two kinds of RIC based on the different time scales: near-real-time RIC (10 milliseconds to 1 second) and non-real-time RIC (more than 1 second). The custom software applications for radio resource management running in the near-real-time RIC and the non-real-time RIC are called xApps and rApps, respectively [28], [29]. In the dynamic 5G SBS networks, user association must be performed near-real-time. Therefore, this paper focuses on the near-real-time RIC and develops the proposed algorithm as an xApp. The near-real-time RIC and xApps can utilize the databases named Radio-Network Information Base (R-NIB), UE-Network Information Base (UE-NIB), and the interface named shared data layer (SDL) to perform user association [28]. The R-NIB can contain information relating to RANs (i.e., SBSs), and the UE-NIB stores a list of UEs and maintains tracking of the UEs' association. The xApps can subscribe to these databases and monitor the user association situation of SBS networks by using SDL.

B. OPTIMIZATION PROBLEM FORMULATION FOR USER ASSOCIATION

In the SBS networks, we aim to maximize the utility function of load balancing and find the optimal association in terms of network fairness. We model this problem as a combinatorial optimization problem [30] and solve it using an MCTS-based heuristic algorithm. The sets of SBSs and HDR UEs are denoted by S and hU, respectively. The optimization problem that involves determining the variable $x_{ij} \in \{0, 1\}$, which represents the association result between HDR UE $i \in$ hU and SBS $j \in S$, can be formulated as

$$\max\ U = \sum_{i \in \mathrm{hU}} \sum_{j \in S} x_{ij} \log(R_{ij}) \tag{1a}$$

$$\text{s.t.} \begin{cases} \sum_{j \in S} x_{ij} = 1, \ \forall i \in \mathrm{hU}, \\ x_{ij} \in \{0, 1\}, \forall i \in \mathrm{hU}, \forall j \in S, \end{cases} \tag{1b}$$

where R_{ij} is the data rate of HDR UE i received from SBS j.

$$R_{ij} = \frac{W_s}{\sum_{i \in \mathrm{hU}} x_{ij}} \log_2(1 + SNR_{ij}), \tag{2}$$

$$SNR_{ij} = \frac{P_j G_{ij}}{\sigma_s^2}, \tag{3}$$

where P_j is the transmit power of SBS j, G_{ij} indicates the channel gain between HDR UE i and SBS j, including antenna gain, path loss, and shadowing. σ_s^2 indicates the noise power of SBSs. The SBS networks are assumed to be noise-limited, which implies that HDR UEs are affected by noise rather than interference due to the low transmit power and higher radio channel attenuation of SBSs. The simulation results in [31] confirm this assumption.

We introduce Jain's fairness to evaluate load fairness among SBSs in the same cluster,

$$J = \frac{\left(\sum_{i\in \mathrm{hU}} \sum_{j\in S} x_{ij}R_{ij}\right)^2}{|S| \sum_{j\in S} \left(\sum_{i\in \mathrm{hU}} x_{ij}R_{ij}\right)^2}, \quad \frac{1}{|S|} < J < 1. \tag{4}$$

The path loss model is based on Recommendation ITU-R P.1411-10, which is available in the millimeter-wave bands [32]. It can be applied to the propagation environment of the 0.8-73GHz bands in urban, suburban, and residential areas. We use the urban high-rise ABG path loss model, which corresponds to a hotspot urban environment with many high-rise buildings. This model is applicable to the 0.8-38GHz bands and is represented by the following equation:

$$PL(d, f) = 10\alpha \log_{10}(d) + \beta + 10\gamma \log_{10}(f) + X_\sigma, \tag{5}$$

where d is the distance between the BS and UE, f is the carrier frequency of the BS, and X_σ is the shadow fading term, which follows a log-normal distribution with a standard deviation of σ(dB). The line-of-sight (LOS) and non-line-of-sight (NLOS) parameters are listed in Table 1. To simplify the analysis, we assume that all HDR UEs are in the LOS channel.

TABLE 1. Factors for ITU-R P.1411-10.

	α	β	γ	σ
LOS	2.12	29.2	2.11	5.06
NLOS	4.00	10.2	2.36	7.60

III. ALGORITHM

Algorithm 1 shows one iteration of the MCTS-based user association algorithm, which consists of four steps. The algorithm is iterated to determine the optimal solution.

Algorithm 1 One Iteration of Proposed Algorithm

Selection:
Select the best expandable child node by tree policy
Expansion:
Expand the tree by making a child node on the selected node
Simulation:
Run a Monte Carlo method-based simulation (playout) in the expanded node until all UEs are connected to BS
Backpropagation:
Update the simulation results to upper nodes

The greater the number of iterations, the deeper the tree expands from the root node. A deeper tree implies that more UEs-SBSs combinations can be sampled, increasing the probability of obtaining near-optimal UEs-SBSs combinations. Initially, the root node corresponds to the state in which no HDR UE is offloaded to an SBS. The root node does not yet have a child node, and the expansion step is executed immediately when the root node creates a child node. This child node represents a situation in which an HDR UE (UE1 in Fig. 4) is associated with an SBS.

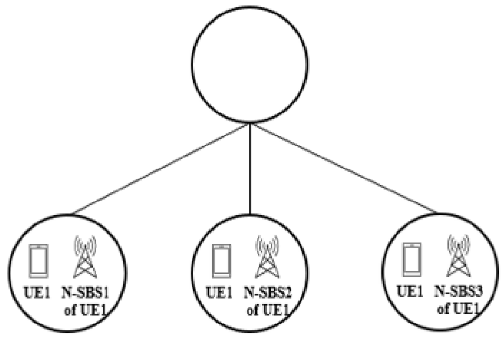


FIGURE 4. Fully expanded root node (number of N-SBS = 3).

UE1 associates with one of its neighboring SBSs (N-SBSs) that provide high received power. The number of N-SBSs is adjustable and should be preliminarily determined before the algorithm is executed. The expanded child node contains UE1 and one of its N-SBSs. This child node immediately runs the simulation step. In this step, under the condition that UE1 associates with the selected N-SBS, all other HDR UEs associate with one of their N-SBSs via random sampling using the Monte Carlo method. Then, we can obtain the network state in which all HDR UEs are associated with one of their N-SBSs. This network state is a random combination of UEs-N-SBSs that does not consider load balancing. The child node stores the network utility in this combination during the backpropagation step.

Next, the root node creates other child nodes, indicating that UE1 is associated with other N-SBSs through expansion. Simulation and backpropagation are also repeated in these child nodes. Then, suppose the root node creates as many child nodes as the predetermined number of N-SBSs. In that case, it becomes a fully expanded node (Fig. 4) and selects a child node to expand according to the tree policy (selection step). High performance is guaranteed when upper confidence bounds for trees (UCT) is applied as a tree policy [21].

$$\mathrm{UCT} = \bar{X}_j + 2C_p\sqrt{\frac{2\ln n}{n_j}} \tag{6}$$

$\bar{X}_j$ is a value between 0 and 1, which indicates the average reward of child node j. In our proposed algorithm, $\bar{X}_j$ is the ratio of the utility value of the corresponding node to the sum of the utility values of all child nodes for which the parent node is the same, including itself. If we ignore the bias term $\sqrt{(2\ln n)/n_j}$, then higher values of $\bar{X}_j$ are associated with a higher probability of the node being selected (exploitation). However, even though the selected child node exhibits good performance, it may not be the best choice when considering the associations of all other HDR UEs. Therefore, the tree must be expanded by exploring multiple nodes (exploration). n is the number of visits to a fully expanded parent node, and n_j in the denominator of the bias term is the number of visits to child node j. The value of the bias term of the less-visited child node increases, and the UCT ensures the exploration of all child nodes. Thus, we can expand the tree while balancing exploitation and exploration using UCT as a tree policy. The exploration constant C_p can be adjusted to encourage or discourage exploration. In Section IV, we determine the optimal C_p value for user associations.

In the selection step, the child node with the highest UCT value is selected, which then becomes the current node. The current node creates a child node through expansion. This child node contains UE2 and one of its N-SBSs. Similarly, this node runs simulation-backpropagation. By this time, the UE1-N-SBS (represented by the parent node) has already been determined, and the association of UE2 (represented by the current node) has been tested. Under these conditions, all remaining HDR UEs are associated with one of their N-SBSs, creating a UEs-N-SBSs combination. In this combination, the network utility of the current node is calculated. In backpropagation, the current node stores this utility value and updates that of all upper nodes, including its parent node. However, the upper nodes already have previously calculated utility values. In this case, in the proposed algorithm, the upper nodes replace their utility values with the average of existing and updated values. The average value is obtained by dividing the cumulative utility, which is the sum of the utility values generated each time backpropagation occurs, by the number of visits.

Starting at the root node, the tree is expanded by the predetermined number of iterations (nIter). However, as mentioned previously, before the root node becomes a fully expanded node, iterations are performed without selection. Fig. 5 shows an example of an expanding tree. After expansion by nIter is completed, the tree returns the child node of the root node with the highest capacity. In other words, among the child nodes containing UE1 and one of its N-SBSs, the tree returns the child node containing the optimal N-SBS in terms of load balancing. If we denote the N-SBS of the returned child node as SBS1*, UE1-SBS1* becomes a new root node and repeats the same MCTS operation. This implies that the MCTS operation is executed, while UE1 is associated with its optimal N-SBS (i.e., SBS1*). In this case, the tree returns to UE2 and its optimal N-SBS. We can obtain the optimal UEs-N-SBSs combination when these operations are repeated for all HDR UEs. The flow chart for the proposed algorithm is summarily shown in Fig. 6.

Thanks to the properties of the MCTS, we only need to explore some combinations of HDR UEs and their N-SBSs. Simultaneously, we can obtain a near-optimal combination that achieves network-wide load balancing. Therefore, our algorithm can significantly reduce the computational complexity while obtaining a near-optimal solution.

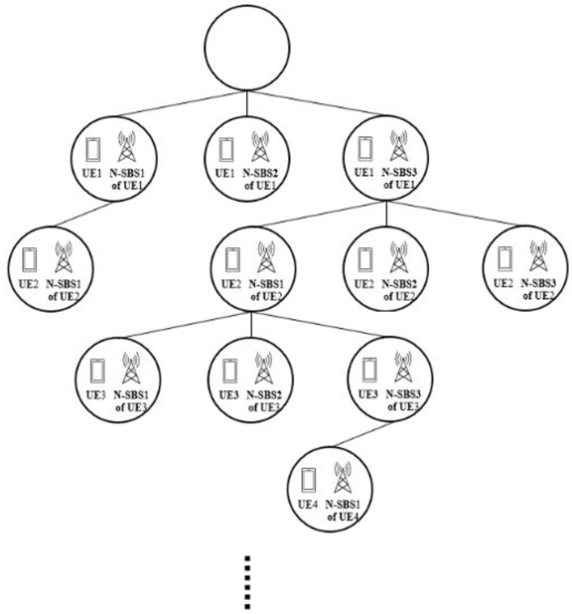


FIGURE 5. Example of an expanding tree.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of our algorithm using Monte Carlo simulations. We perform 1,000 simulations for random networks. In each simulation run, UEs and BSs are randomly distributed according to the simulation scenario. We consider a scenario where the RIC performs user association for one of the SBS clusters it manages using the proposed algorithm. To evaluate the effectiveness of load balancing, we present the average data rates of the bottom 50% of HDR UEs (B-50 HDR UEs) and that of the top 50% of HDR UEs (T-50 HDR UEs) instead of showing the average data rates of all UEs. This is because the overall average data rates can be influenced by UEs monopolizing resources, making it challenging to reflect accurately the load balancing effect.

We compare the performances of the proposed scheme with two conventional user association schemes: CRE and random association. In the simulation scenario, an RIC controls an SBS cluster, and UEs are distributed inside it. The comparison and performance analysis of our algorithm are conducted in different network environments. The simulation parameters are summarized in Table 2.

A. PERFORMANCE COMPARISONS WITH CONVENTIONAL SCHEMES

We compare our algorithm with CRE and random association by changing adjustable parameters. 10 SBSs are randomly distributed in an SBS cluster, and the number of UEs is changed. First, we change the number of N-SBSs (called load balancing level and abbreviated as LBL hereafter) of the proposed scheme and random association. Since CRE does not consider several N-SBSs, the LBL of CRE can

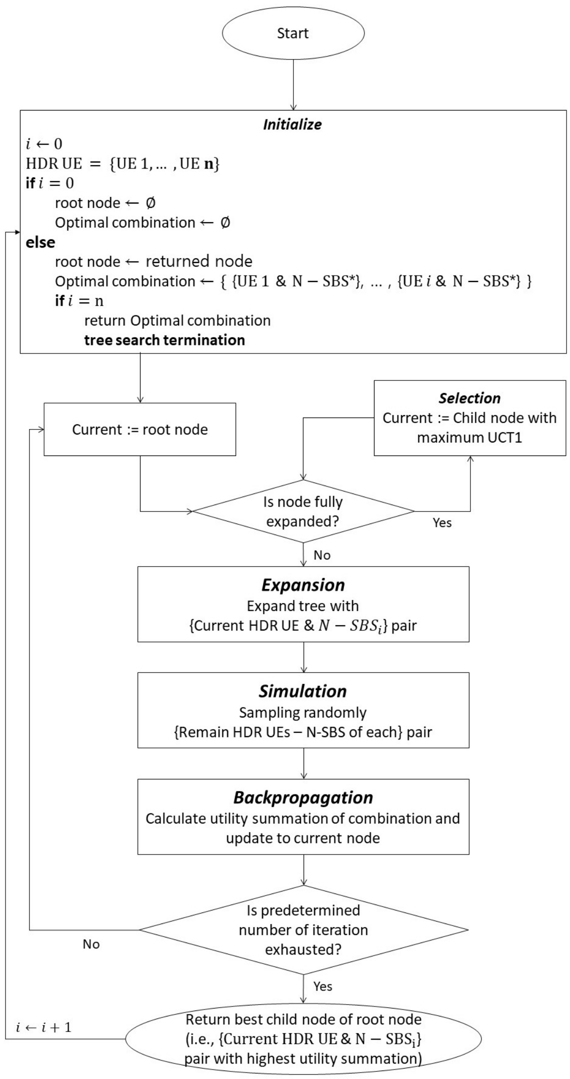


FIGURE 6. Algorithm flowcharts of MCTS for user association.

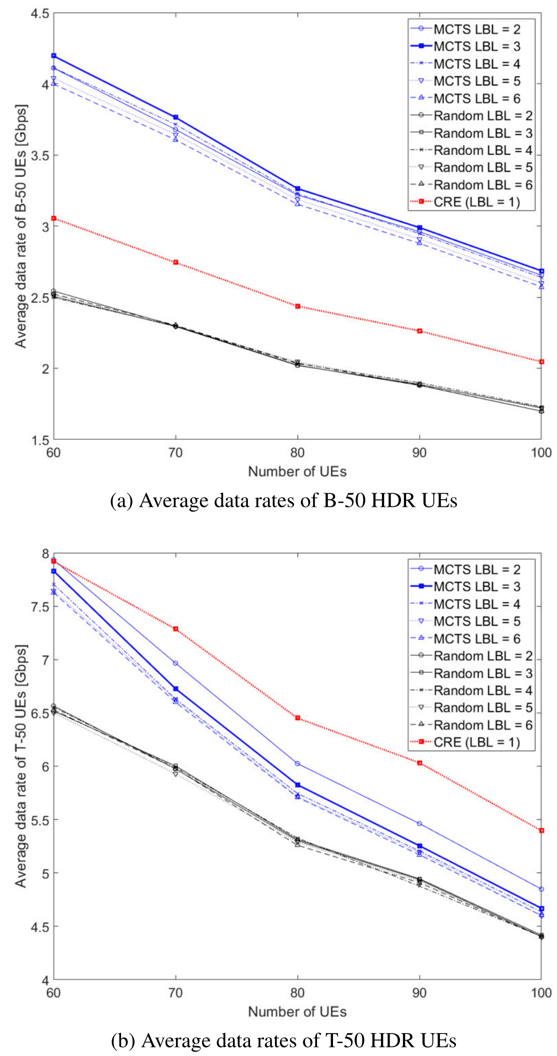


FIGURE 7. Average data rates for different LBLs against the number of UEs using 10 SBSs.

TABLE 2. Simulation parameters and values.

Parameter	Value
Area of one SBS network	100m × 100m
SBS transmit power (P_s)	30dBm
SBS antenna gain (G_s)	18dBi
SBS carrier frequency (f_s)	28GHz
SBS bandwidth (W_s)	800MHz
Noise power of SBS (σ_s^2)	-174dBm/Hz $+10\log_{10} W_s$
Path loss model	ITU-R P.1411-10
Ratio of HDR UE	30%

assumed to be 1. The nIter of the tree is set to LBL ×100. This ensures that the trees for each LBL have similar depths and guarantees the fairness of the performance for different LBLs. Second, we increase the value of nIters for the best LBL and compare it with the result of the optimal solution.

In Fig. 7(a) and 7(b), the average data rates of B-50 HDR UEs and T-50 HDR UEs for different LBLs are shown versus the number of UEs in an SBS cluster for these three schemes, respectively. As shown in Fig. 7(a), the proposed scheme outperforms the benchmark schemes and achieves higher average data rates of B-50 HDR UEs, where random association shows the worst performance. The proposed scheme shows the best performance when LBL=3 and slightly decreases when increasing the number of LBLs beyond 3. This is because the HDR UEs can be offloaded to more distant N-SBSs. Fig. 7(b) presents that by decreasing the LBL, more resources are allocated to T-50 HDR UEs, and their average data rates are also increased. We can realize from these figures that the proposed algorithm with appropriate LBL can effectively distribute resources from T-50 HDR UEs to B-50 HDR UEs.

Fig. 8 shows the SBS load fairness indices against the number of UEs. As shown in Fig. 8, the proposed algorithm has significantly higher fairness indices than other schemes. Also, for LBL = 3, unlike the benchmark schemes, which show rapid changes in the number of UEs, our scheme

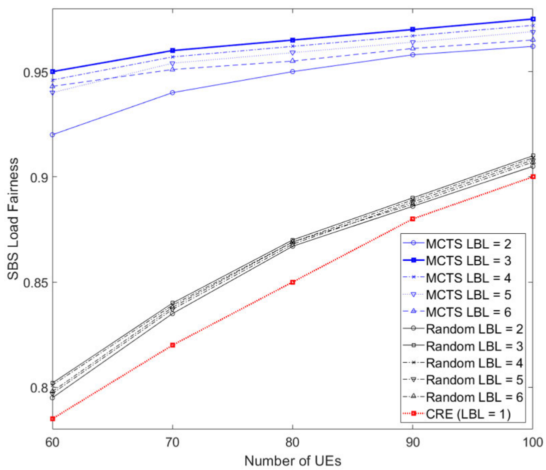


FIGURE 8. SBS load fairness indices for different LBLs against the number of UEs using 10 SBSs.

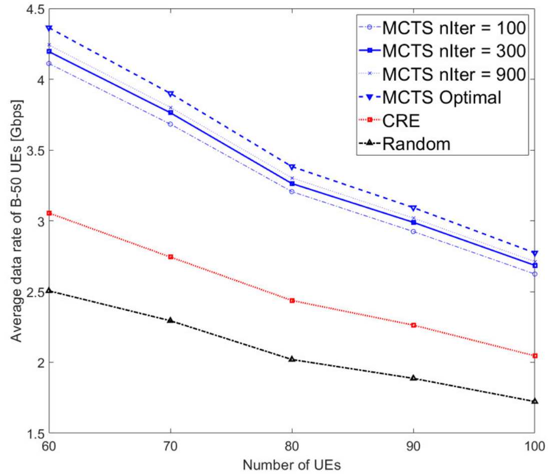
maintains near-optimal fairness. The CRE scheme has the lowest SBS fairness indices because it associates UEs with the N-SBS providing the highest biased power without considering the loads of N-SBS. The random association has slightly higher fairness indices than CRE. However, there are substantial gaps compared to the proposed algorithm that derives the near-optimal UEs-N-SBSs combination in terms of fairness.

Fig. 9 represents the effect of nIters on the HDR UEs for LBL = 3 against the number of UEs using 10 SBSs. As shown by Fig. 9, as nIter of the proposed algorithm increases, the average data rates of B-50 HDR UEs and T-50 HDR UEs increase significantly at nIter = 300 and converge to the optimal value. The nIter = 300 and optimal solution are compared in Table 3 and Table 4. The performance gaps between the optimal solution and nIter = 300 for B-50 UEs and T-50 UEs do not exceed 4% and 2%. Therefore, the simulation results prove that we can obtain a near-optimal solution just by using nIter = 300 and that the proposed algorithm can solve the NP-hard combinatorial optimization problem with reasonable complexity. Also, this result indicates that nIter = LBL ×100, as applied in Fig. 7, is appropriate. Fig. 10 presents the impact of nIters on the SBS load fairness. We can see that the proposed scheme always outperforms the conventional schemes.

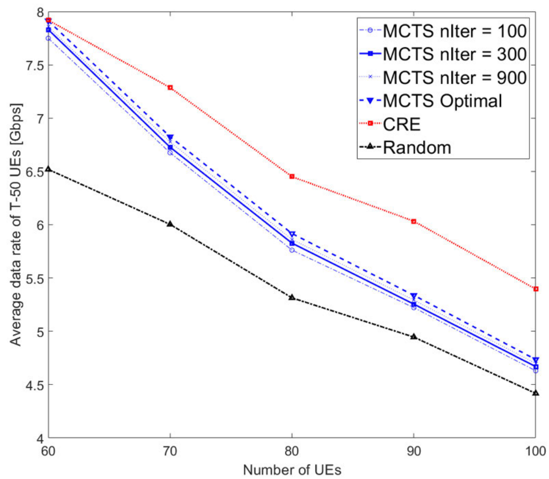
TABLE 3. Numerical analysis of Fig. 9(a).

Number of UEs	nIter = 300 (Gbps)	Optimal (Gbps)	Gap between 300 & Opt. (%)
60	4.205	4.364	3.78
70	3.763	3.900	3.64
80	3.263	3.383	3.68
90	2.989	3.093	3.48
100	2.685	2.773	3.28

Fig. 11 depicts the average data rates of B-50 HDR UEs and T-50 HDR UEs for five different C_p values versus the number of UEs with LBL = 3 and nIter = 300. The $C_p = 0$



(a) Average data rates of B-50 HDR UEs



(b) Average data rates of T-50 HDR UEs

FIGURE 9. Average data rates for different nIters against the number of UEs using 10 SBSs and LBL = 3.

TABLE 4. Numerical analysis of Fig. 9(b).

Number of UEs	nIter = 300 (Gbps)	Optimal (Gbps)	Gap between 300 & Opt. (%)
60	7.830	7.913	1.06
70	6.727	6.825	1.46
80	5.827	5.917	1.54
90	5.255	5.338	1.50
100	4.669	4.736	1.43

implies that the tree expands without exploration. It is interesting to note that even with $C_p = 0$, it shows better performance than CRE. The C_p values greater than 0.01 significantly improve performance, with $C_p = 0.01$ indicating optimal performance. The average data rates are slightly degraded when the C_p value is above 0.01. It is demonstrated that the proposed algorithm requires an appropriate C_p value for optimal user association.

In Fig. 12, the average data rates are shown according to the number of SBSs for three schemes. From Fig. 12(a), even in denser SBS deployment scenarios, we can see that the

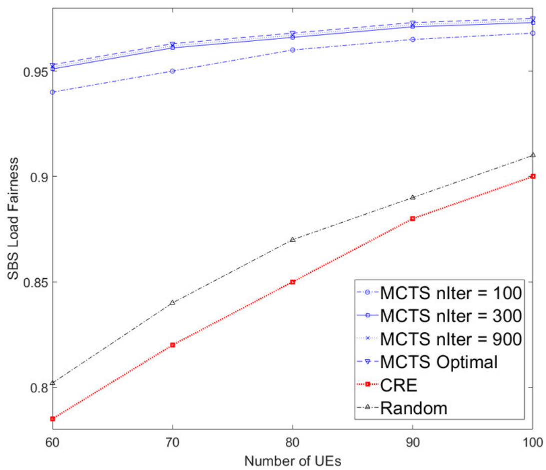
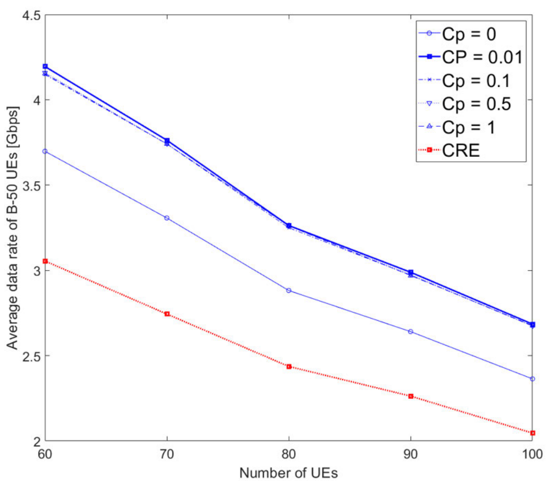
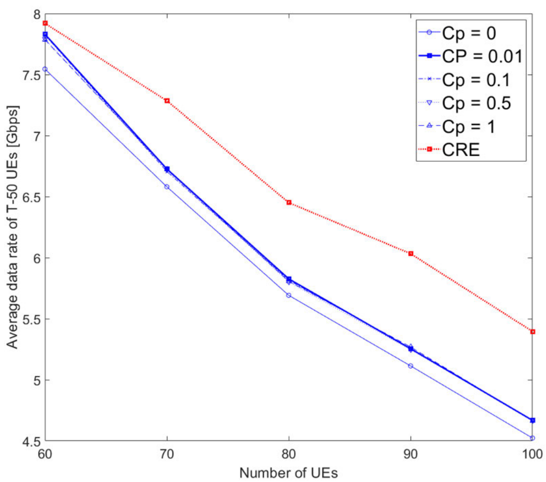


FIGURE 10. SBS load fairness indices for nIters.

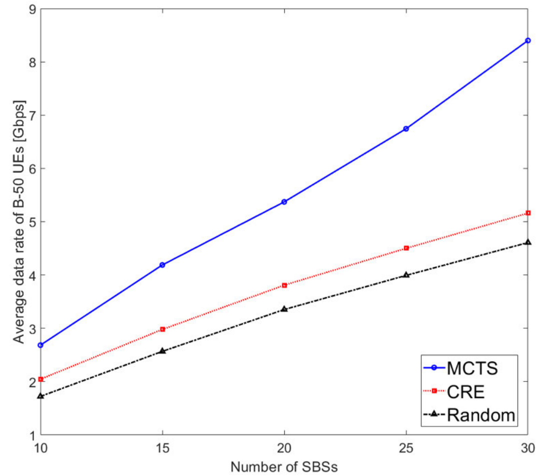


(a) Average data rates of B-50 HDR UEs

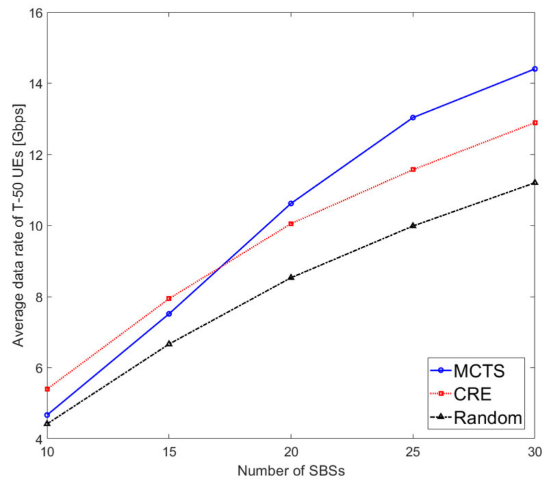


(b) Average data rates of T-50 HDR UEs

FIGURE 11. Average data rate comparisons of C_p value against the number of UEs using 10 SBSs, LBL = 3, and nIter = 300.



(a) Average data rates of B-50 HDR UEs



(b) Average data rates of T-50 HDR UEs

FIGURE 12. Average data rate comparisons against the number of SBSs using 100 UEs (30 HDR UEs), LBL = 3, and nIter = 300.

proposed algorithm delivers superior performance to B-50 HDR UEs. Fig. 12(b) depicts the average data rate of T-50 HDR UEs in densely deployed SBS clusters. Interestingly, this figure presents that as the amount of resources increases, the average data rates of the proposed scheme are greater than that of conventional schemes with the number of SBSs above 20. This result indicates that the proposed algorithm will be useful in future network configurations for THz communications that require numerous SBSs [33]. Fig. 13 shows that the SBS load fairness indices of all compared schemes are decreased as the number of SBSs increases. This is because an increase in the number of SBSs leads to a corresponding increase in the number of vacant SBSs and high variety of loads [14]. In Fig. 13, with any number of SBSs, the proposed scheme always outperforms the conventional user association schemes.

B. TIME COMPLEXITY ANALYSIS

MCTS-based algorithms can consider a subset of the search area so that the time complexity is much less than full

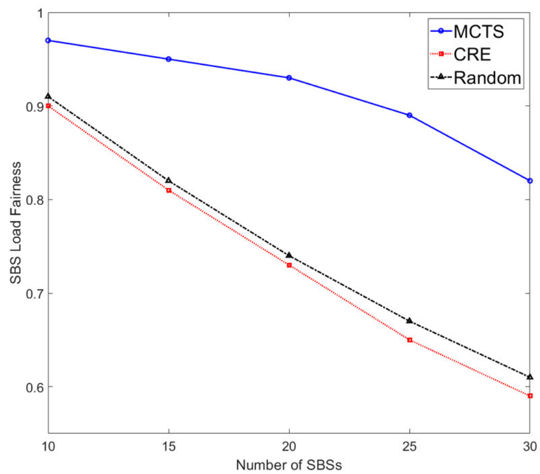


FIGURE 13. SBS load fairness indices for the number of SBSs.

search [34]. The time complexity of MCTS depends on three parameters: nIter, the number of child nodes (i.e., LBL), and the number of HDR UEs. Thanks to the scalability and flexibility of RICs, we can adjust these parameters according to the desired performance, as shown in the above simulation results. It is also worth mentioning that increasing the available RIC resources can significantly expand the number of UEs by effectively managing the SBS clusters. Table 5 shows the running time for the number of HDR UEs within one SBS cluster when our algorithm is executed on an AMD Ryzen 9 5900X 12-Core Processor 3.70 GHz. Despite the limited computing resources, the computation time for nIter = 300 is less than one second. We expect that our algorithm will be applicable to O-RAN architecture as an xApp for near-real-time RIC [35].

TABLE 5. Running time of proposed algorithm with LBL = 3, nIter = 300.

Number of HDR UEs (UEs) within one cluster	Running time of proposed algorithm with nIter = 300[ms]
18 (60)	340
21 (70)	460
24 (80)	560
27 (90)	670
30 (100)	790

V. CONCLUSION

In this paper, we proposed a centralized user association scheme based on MCTS to achieve load balancing and maximize load fairness. Our goal is to maximize the average data rate of B-50 HDR UEs by distributing the resources consumed by the T-50 HDR UEs. The network environment with an SBS cluster managed by RIC and the performance for the number of UEs and SBSs are considered. The problem is an NP-hard combinatorial optimization problem that is solved by an MCTS-based user association algorithm with appropriate parameters. The performance of our proposed method was compared with the CRE scheme and random association scheme. Numerical results showed that the proposed scheme outperforms conventional user association schemes while providing near-optimal solutions with reasonable computational complexity. In addition, our algorithm showed better performance than CRE and random association schemes, even in the network with more densely deployed SBSs. Computation time analysis indicated that the time complexity of our scheme can be sufficiently supported by the near-real-time RIC of the O-RAN architecture and that our algorithm can be deployed in practical systems of the future network. We hope our algorithm will provide a practical solution to the long-standing user association problem.

REFERENCES

[1] M. Kamel, W. Hamouda, and A. Youssef, "Ultra-dense networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2522–2545, 4th Quart., 2016.

[2] T. Zhang, J. Zhao, L. An, and D. Liu, "Energy efficiency of base station deployment in ultra dense HetNets: A stochastic geometry analysis," *IEEE Wireless Commun. Lett.*, vol. 5, no. 2, pp. 184–187, Apr. 2016.

[3] Y. Li, Y. Zhang, K. Luo, T. Jiang, Z. Li, and W. Peng, "Ultra-dense HetNets meet big data: Green frameworks, techniques, and approaches," *IEEE Commun. Mag.*, vol. 56, no. 6, pp. 56–63, Jun. 2018.

[4] J. An, K. Yang, J. Wu, N. Ye, S. Guo, and Z. Liao, "Achieving sustainable ultra-dense heterogeneous networks for 5G," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 84–90, Dec. 2017.

[5] J. S. Perez, S. K. Jayaweera, and S. Lane, "Machine learning aided cognitive RAT selection for 5G heterogeneous networks," in *Proc. IEEE Int. Black Sea Conf. Commun. Netw. (BlackSeaCom)*, Istanbul, Turkey, Jun. 2017, pp. 1–5.

[6] Y. Zhang, L. Xiong, and J. Yu, "Deep learning based user association in heterogeneous wireless networks," *IEEE Access*, vol. 8, pp. 197439–197447, 2020.

[7] D. Liu, L. Wang, Y. Chen, M. Elkashlan, K.-K. Wong, R. Schober, and L. Hanzo, "User association in 5G networks: A survey and an outlook," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1018–1044, 2nd Quart., 2016.

[8] S. Corroy, L. Falconetti, and R. Mathar, "Dynamic cell association for downlink sum rate maximization in multi-cell heterogeneous networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2012, pp. 2457–2461.

[9] J. G. Andrews, S. Singh, Q. Ye, X. Lin, and H. S. Dhillon, "An overview of load balancing in HetNets: Old myths and open problems," *IEEE Wireless Commun.*, vol. 21, no. 2, pp. 18–25, Apr. 2014.

[10] K. Okino, T. Nakayama, C. Yamazaki, H. Sato, and Y. Kusano, "Pico cell range expansion with interference mitigation toward LTE-advanced heterogeneous networks," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC)*, Jun. 2011, pp. 1–5.

[11] N. Bhushan, J. Li, D. Malladi, R. Gilmore, D. Brenner, A. Damnjanovic, R. T. Sukhavasi, C. Patel, and S. Geirhofer, "Network densification: The dominant theme for wireless evolution into 5G," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 82–89, Feb. 2014.

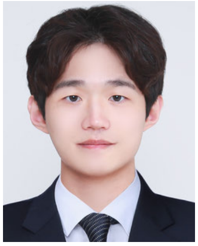
[12] A. Damnjanovic, J. Montojo, Y. Wei, T. Ji, T. Luo, M. Vajapeyam, T. Yoo, O. Song, and D. Malladi, "A survey on 3GPP heterogeneous networks," *IEEE Wireless Commun.*, vol. 18, no. 3, pp. 10–21, Jun. 2011.

[13] G. Sun, K. Xiong, G. O. Boateng, G. Liu, and W. Jiang, "Resource slicing and customization in RAN with dueling deep Q-network," *J. Netw. Comput. Appl.*, vol. 157, May 2020, Art. no. 102573.

[14] E. M. Mohamed, S. Hashima, K. Hatano, E. Takimoto, and M. Abdel-Nasser, "Load balancing multi-player MAB approaches for RIS-aided mmWave user association," *IEEE Access*, vol. 11, pp. 15816–15830, 2023.

[15] Y. Zhang, K. Sun, X. Gao, W. Huang, and H. Zhang, "Load balancing and user association based on historical data," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2021, pp. 1–6.

[16] M. Zarifneshat, P. Roy, and L. Xiao, "Multi-objective approach for user association to improve load balancing and blockage in millimeter wave cellular networks," *IEEE Trans. Mobile Comput.*, vol. 22, no. 5, pp. 2818–2836, May 2023.
[17] B. Lim and M. Vu, "Distributed multi-agent deep Q-learning for load balancing user association in dense networks," *IEEE Wireless Commun. Lett.*, vol. 12, no. 7, pp. 1120–1124, Jul. 2023.
[18] B. Balasubramanian, E. S. Daniels, M. Hiltunen, R. Jana, K. Joshi, R. Sivaraj, T. X. Tran, and C. Wang, "RIC: A RAN intelligent controller platform for AI-enabled cellular networks," *IEEE Internet Comput.*, vol. 25, no. 2, pp. 7–17, Mar. 2021.
[19] *O-RAN E2 Service Model (E2SM), RAN Control–V3.00*, O-RAN Working Group 3, Alfter, Germany, 2022.
[20] S. Bayat, R. H. Y. Louie, Z. Han, B. Vucetic, and Y. Li, "Distributed user association and femtocell allocation in heterogeneous wireless networks," *IEEE Trans. Commun.*, vol. 62, no. 8, pp. 3027–3043, Aug. 2014.
[21] C. B. Browne, E. Powley, D. Whitehouse, S. M. Lucas, P. I. Cowling, P. Rohlfshagen, S. Tavener, D. Perez, S. Samothrakis, and S. Colton, "A survey of Monte Carlo tree search methods," *IEEE Trans. Comput. Intell. AI Games*, vol. 4, no. 1, pp. 1–43, Mar. 2012.
[22] M. Yan, G. Feng, J. Zhou, and S. Qin, "Smart multi-RAT access based on multiagent reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4539–4551, May 2018.
[23] Y. Azimi, S. Yousefi, H. Kalbkhani, and T. Kunz, "Applications of machine learning in resource management for RAN-slicing in 5G and beyond networks: A survey," *IEEE Access*, vol. 10, pp. 106581–106612, 2022.
[24] *O-RAN: Towards an Open and Smart RAN*, O-RAN Alliance, Alfter, Germany, 2018.
[25] M. Wang, J. Chen, E. Aryafar, and M. Chiang, "A survey of client-controlled HetNets for 5G," *IEEE Access*, vol. 5, pp. 2842–2854, 2017.
[26] A. S. Abdalla, P. S. Upadhyaya, V. K. Shah, and V. Marojevic, "Toward next generation open radio access networks: What O-RAN can and cannot do!" *IEEE Netw.*, vol. 36, no. 6, pp. 206–213, Nov. 2022.
[27] *LTE Physical Layer Framework for Performance Verification*, document R1-070674, 3GPP, 2013.
[28] *Near-RT RIC Architecture–V4.00*, O-RAN Working Group 3, Alfter, Germany, 2023.
[29] *Non-RT RIC Architecture–V3.00*, O-RAN Working Group 2, Alfter, Germany, 2023.
[30] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. G. Andrews, "User association for load balancing in heterogeneous cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 2706–2716, Jun. 2013.
[31] H. Elshaer, M. N. Kulkarni, F. Boccardi, J. G. Andrews, and M. Dohler, "Downlink and uplink cell association with traditional macrocells and millimeter wave small cells," *IEEE Trans. Wireless Commun.*, vol. 15, no. 9, pp. 6244–6258, Sep. 2016.
[32] *Propagation Data and Prediction Methods for the Planning of Short-Range Outdoor Radiocommunication Systems and Radio Local Area Networks in the Frequency Range 300 MHz to 100 GHz*, document Recommendation ITU-R P.1411-10, 2019.
[33] E.-K. Hong, "6G R&D vision: Requirements and candidate technologies," *J. Commun. Netw.*, vol. 24, no. 2, pp. 232–245, Apr. 2022.
[34] M. L. Littman, "Reinforcement learning improves behaviour from evaluative feedback," *Nature*, vol. 521, no. 7553, pp. 445–451, May 2015.
[35] *O-RAN Architecture Description–V9.00*, O-RAN Working Group 1, Alfter, Germany, 2023.



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