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RESEARCH ARTICLE

Interference Mitigation in mmWave Heterogeneous Cloud-Radio Access Network: For Better Performance and User Connectivity

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ABSTRACT The rapid advancements in wireless communications have prompted a surge in mobile data traffic, necessitating innovative solutions for 5G and beyond. This paper introduces a two-tier Heterogeneous Cloud Radio Access Network (HC-RAN) model leveraging millimeter Wave (mmWave) and sub-6 GHz frequencies to address this need. It integrates User-RRH associations to mitigate interference, enhance network throughput (via Heuristic Algorithm) and RRH-BBU clustering (via k-means) to manage resources in the network. The study evaluates SINR and rate coverage probabilities across various deployment scenarios, including Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions, as well as random and edge-based deployments. Results demonstrate that strategic placement of Remote Radio Heads (RRHs) and efficient clustering significantly improve network efficiency and user connectivity. In LOS conditions, random RRH deployments deliver superior coverage and throughput due to spatial diversity and reduced path loss. Conversely, edge-based deployments necessitate more resources to handle traffic demands but can excel in controlled scenarios. The proposed joint User-RRH association with RRH-BBU k-means clustering algorithm effectively manages interference, also maintains a balance between quality of service and efficient resource management. The proposed User-RRH association sub problem scheme that based on minimum path loss as a basic criterion outperforms on Limited Capacity User-RRH Association scheme (LC UA) in both the random and edge deployment scenarios and yield increasing in average throughput by approximately 38% and 27%, respectively. In other hand, the adaptive solution of RRH-BBU k-means clustering sub problem depend on actual load and number of active RRHs in the network to find the number of k RRH-BBU clusters, which manage resource consumption. This highlights the challenges in resource allocation and management with and without clustering. This paper concludes that optimized cell site deployment combined with association and clustering algorithms can significantly enhance 5G network performance, particularly in dense urban environments. These insights help network operators balance high service quality with efficient resource utilization.

INDEX TERMS Millimeter wave (mmWave), heterogeneous cloud-radio access network (HC-RAN), line-of-sight (LOS), non-line-of-sight (NLOS), user association, k-means clustering.

I. INTRODUCTION

The rapid progress of wireless communications technological in recent years, in posing challenges for fifth generation (5G) networks in contend with explosive growth in traffic for mobile data due to the proliferation of different personal computing devices, including laptops, smartphones and smart-wearable technology devices, as well as a huge number of data intensive mobile apps, that will push the capability of the current system beyond the maximum [1].

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To meet this booming demand, a millimeter Wave (mmWave) is an attractive option to address future capacity deficiency. One of the distinguishing features of mmWave is its broad bandwidth in comparison with sub-6 GHz, which can significantly enhance cellular network capacity and make- mmWave mmWave communication an essential technology due to the bandwidth that extends from 30- 300GHz but these frequencies have a short range and are intermittent in nature, because they experience from some impacts such as blockage and severe path losses [2], [3].

Within this paradigm, the Cloud Radio Access Network (C-RAN) is emerging as a pivotal architecture promising to optimize use of mmWave spectrum and improve performance in 5G and future wireless networks. As Base Band Unit (BBU), and Remote Radio Head (RRH) are the two components that will comprise the traditional base station, as RRHs are distributed over across multiple locations. While BBUs controller are grouped in a cloud pool, which contains all information about the network. Moreover, the RRHs are linked to the BBUs via various technologies, including fiber optic cables, or wireless links, depending on the specific deployment scenario and network requirements. The network information is periodically updated based on user reports obtained through the associated RRHs. The location coordinates and coverage region of all RRHs are also known to the controller. The BBU controller runs the algorithms for performing handover and association decisions, which are then transmitted to the RRHs. So, C-RAN is considered a cost-effective option for network densification and reduce resource consumption and interference management in future communication networks [4].

In the early deployment of mmWave cellular communications and in dense urban environments, Heterogeneous Cloud Radio Access Networks (HC-RANs) are most useful for improving network performance through the deployment of ultra-dense mmWave small base stations (SBSs) and their coexistence with conventional Microwave base station (MBS) in a multi-band heterogeneous network architecture [1].

Despite this, such adaptation is costly and poses complex challenges, such as the implementation of incremental deployment for the architecture of heterogeneous networks and the creation of different technology paradigms, in addition to the high frequency and unique propagation characteristics of mmWave signals, which result in unprecedented levels of interference between cells especially at the cell edge [5].Therefore, designing efficient schemes for interference management is critical, and without a doubt, it is a hot research topic [6].

Along with rapid progress in technology in recent years, advances in communications technology have been accompanied by a swift expansion of machine learning (ML) applications in wireless networks. This growth is largely due to the speed and efficacy of ML, particularly for large-scale challenges. Machine learning has become an integral part of 5G networks and is expected to be a major driver of upcoming mobile and 6G technologies in the future [7].

The contributions of this paper can be outlined as follows:

- Represent, verify and evaluate a two tier HC-RAN system in terms of different performance criteria depending on actual load in network and type of deployment scenarios, using different frequency range to serve each tier to mitigate the interference, and improve rate and coverage, not only in the edge area but throughout the cell area.
- Develop a unique hybrid algorithm that combines a novel approach User-RRH association (via Adaptive Heuristic Algorithm by selecting RRH that offer the minimum pathloss linkage to form associations) and RRH-BBU clustering (via k-means Clustering Algorithm for RRHs clustering to find the number of k RRH-BBU clusters) in mmWave HC-RAN Networks. As a result of this combination of the good deployment scenario in the proposed network with the joint algorithm, several types of interference were reduced as: (Inter-tier Interference, and Inter-RRHs Interference) in addition to increasing the throughput in User-RRH association and RRH-BBU Clustering to reduce resource consumption. This method optimizes the distribution of users across BBUs while taking into account SINR thresholds, spectral efficiency, and resource allocation, thus improving the Quality of Service (QoS) for end users, which enhances the network's overall performance.
- Formulates the joint optimization problem as a mixed-integer non-linear programming problem and successfully decomposes it into two sub-problems for efficient solution, and to demonstrates the effectiveness of the proposed solutions through simulation results, showcasing improved network utility and it performance.

The rest of the paper is organized as follows: Section II presents related work. Section III describes the system model in terms of network deployment, channel and path loss model. In section IV performance metrics was described, which include the coverage probability, rate, and network throughput & optimization problem formulation. Section V and VI described simulation implementation, results and discussions for SINR coverage probability analysis, rate coverage probability, and the joint solution of user association and RRHS k-mean clustering optimization. Section VII conclusion. Finally, in section VII we conclude the paper.

II. RELATED WORK

The study of interference management and mitigation have been addressed in various literatures.

In [8], the authors analyzed the Coverage in K-tier downlink mmWave HC-RAN with user centric small cell deployments; they find that when the transmit power of large-cell base stations is fixed, increasing the transmit power of small-cell base stations can result in a higher likelihood of coverage by taking into account the association relationship between users' and BSs' locations, and take into consideration the unique characteristics of mmWave communications, such as directional beamforming and an advanced path loss model that accounts for both line-of-sight (LOS) and non-line-of-sight (NLOS) broadcasts. with an emphasis on methods for mitigating interference in order to enhance user connectivity and performance.

In [9], an extensive and comprehensive survey explores different RAN architectures in the context of 5G is presented, which includes C-RAN, HC-RAN, virtualized C-RAN, and fog-RAN. The architectures are compared from multiple perspectives, including system architecture, operational expenditure, resource allocation, energy consumption, spectrum efficiency, and network performance. Additionally, the survey reviews key enabling technologies for 5G systems, including, massive multi-input multi-output, millimeter wave, massive machine type communication, and device-to-device communication; in order to identified several of potential avenues for future research related to 5G RANs and RATs, to inspire the community to pursue practical solutions using cutting-edge technology.

The authors in [1], proposed a scheme to increase the data rate in in conventional macrocell regions by utilizing the wide mmWave spectrum. This approach drew inspiration from the Soft Frequency Reuse (SFR) technique, segmenting the cell region into an internal region (a conventional macrocell) and an outer region consisting of small-sized mmWave RRHs positioned at the cell edges within a HC-RAN structure. Different frequency ranges were assigned to each region. Given that the cell edge areas typically experience lower coverage rates due to high interference levels and low received power, these regions were served by the mmWave band. By deploying mmWave cells in these areas, user throughput was enhanced, and spectral efficiency, data rates, and coverage were improved not only at the cell edges but throughout the entire cell area. Additionally, the authors employed a clustering algorithm, designed as a box-packing problem, to group adjacent RRHs together.

By employing stochastic geometry techniques, authors in [3] analyzed the performance of 5G communication networks where macro base stations operate at sub-6 GHz frequencies, and small base stations function within the mmWave frequency range. They derived the cell association probability based on various cell association biases, resulting in expressions for small base stations line-of-sight (LOS) and non-line-of-sight (NLOS) association probabilities. These expressions can be used to adjust the load distribution among different tiers of base stations. Furthermore, to mitigate intra-cell interference in ultra-dense mmWave networks, they proposed a clustering technique. This method selects certain small base stations that provide the minimum path loss connections to form a cluster.

The authors in [10] presented a machine learning-based technique for mitigating inter-beam and inter-cell interference in 5G networks that utilize mmWave technology. Their approach focused on optimizing resource allocation and user-cell association to improve the overall sum rate of the network. They employed a machine learning algorithm that incorporated a workspace for managing user-cell association and power allocation between packets.

A proposal for a mmWave full-duplex C-RAN for 5G systems and beyond was introduced in [2]. The study evaluated the effectiveness of mmWave using the RRH selection method for both half-duplex and full-duplex mmWave C-RAN configurations, focusing on the end-to-end signal-to-interference-plus-noise ratio (SINR). This evaluation considered the path loss, obstructions, and directivity of both fronthaul (FH) and access links, as well as the instantaneous characteristics of the mmWave channel. Additionally, the effectiveness of the RRH selection approach was validated through Monte Carlo simulations, which demonstrated a significant improvement in performance.

In [11] Because of the extremely dense small cells, inter-cell interference was eliminated by the 5G framework's implementation of cloud computing. The authors suggested an enhanced version of the cat swarm optimization algorithm, which was executed by the host management entity in order to determine the optimal BBU-RRH combination across all RRHs inside the network, minimize call blocking, and resolve the load balancing optimization issue. Following a quality-of-service (QoS) examination for each new BBU-RRH combination, optimization is performed on each user. Additionally, the evaluation was carried out with regard to throughput, response time, and blockage probability.

The authors in [12] tackled the challenge of joint user association (UA) and remote radio head (RRH) clustering (RC) in Cloud-Radio Access Networks (C-RAN) with the goal of maximizing throughput while minimizing power consumption. Their approach involved decomposing the joint problem into two more manageable sub-optimization problems. Firstly, they addressed the UA sub-problem using a non-cooperative game model. Secondly, the RC sub-problem was approached through cooperative game theory, employing heuristic solutions based on split and merge rules to enhance network utility. These sub-problems were resolved sequentially and iteratively until convergence was achieved.

The authors in [13] explored the various applications of mmWave technology. To tackle the complexity of interference control, they introduced a novel strategy called Multi-Agent Context Learning. This approach successfully maintained low interference levels even during heavy traffic by using Contextual Bandit techniques to manage interference and allocate mmWave beams in the network. By leveraging the knowledge of neighboring beam statuses, the machine learning agent was able to identify and avoid potential interference with other ongoing transmissions.

In this paper, we used a system model somewhat similar to the model in [1], where the model took inspiration from the Soft Frequency Reuse method, where the cell area was divided into: center region (a conventional macrocell) and edge region (mmWave smallcells) in an HC-RAN structure. A different frequency range was used to serve each region to mitigate the interference, and improve rate and coverage, not only in the edge area but throughout the cell area. But we used both the UMa and UMi-street canyon together in this network for channel models scenarios adopted in 3GPP TR 38.901 [14]. To our knowledge, the UMa and UMi-street canyon scenarios have never before been implemented together in a same two-tier heterogeneous wireless network. UMa is assigned to the first tier, which operates at frequencies sub-6 GHz, while UMa is assigned to the second tier, which operates at mmWave frequencies.

The objectives of this paper are to verify and evaluate the performance of the proposed system in terms of different performance criteria and present a method to mitigate interference and obtain better network throughput in exchange for reducing resource consumption using user association and RRHs clustering, thus improving the Quality of Service (QoS) for end users.

In order to mitigate interference, we adopted a dual strategy that simultaneously improves user association and RRHs clustering, as in [12], where they addressed the issue of user association and RRHs clustering. Where they suggested breaking up the problem into two smaller sub-optimization problems: the user association and RRHs clustering, this was addressed by applying heuristic solutions. But instead of the heuristic solutions, we used the clustering method as in [3] to form associations between RRHs and users by selecting RRHs that offer the minimum pathloss linkage instead of maximum SINR to form associations with users for the purpose of eliminating RRH interference, and for RRH-BBU associations, we used K-means clustering, unlike traditional k-means clustering, which is static, our approach adapts the clustering process based on real-time interference patterns [15] instead of a heuristic solution for RRHs clustering to find the number of clusters, k, using a data-driven approach (number of Users and RRHs).

III. SYSTEM MODEL

A. NETWORK DEPLOYMENT

The proposed model is a two tier HC-RAN system are deployed in Ultra Dense Networks (UDNs), its first tier composed of high power macrocells arranged in a hexagonal grid served by macro Base stations, which provide broad coverage and support for high mobility. They are responsible for ensuring basic connectivity and coverage over a large area and serve users at greater distances. Typically located at higher altitudes and equipped with higher transmission power. While the second tier composed of low power smallcells served by mmWave RRHs, which enhance capacity and coverage within smaller, more densely populated areas. They are often deployed to improve network performance in hotspots or areas with high user density. Typically deployed at lower altitudes (e.g., on rooftops or street furniture) and have lower transmission power compared to macro Base stations. The RRHs organized in clusters, where each cluster is composed of N RRHs that are geographically close to each other distributed at points on macrocells to cover the whole cell areas. RRHs need to manage a higher density of users and often deal with more complex interference scenarios due to their proximity to users and other cells [1].

In order to improve resource utilization and address the frequent handover and blockage of the mmWave channel in C-RAN, the BBUs are separated from the RRHs and gathered into a centralized BBU pool controller. From there, the BBUs collaborate and coordinate in the central cloud, while RRHs are placed on the cells positions and linked to the BBU pool via front haul.

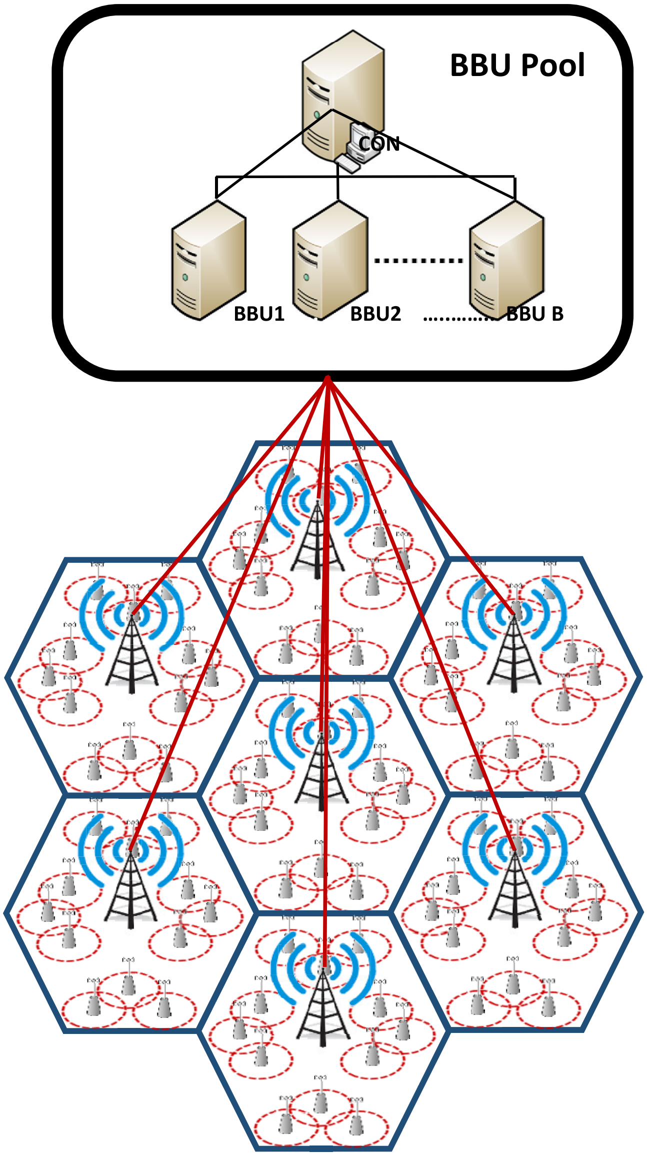


FIGURE 1. Network deployment.

The coordination and management between tiers aims to efficiently distribute network traffic between macro base stations and RRHs to avoid congestion and optimize resource utilization. This is met with the challenge of determining which users should be served by macro base stations or RRHs based on factors such as signal quality, capacity, and user demand. This requires real-time decision-making and prediction algorithms to adapt to changing conditions. All this is done in the BBU pool controller, where smallcells (RRHs) of mmWave HC-RANs are accessed over wireless fronthaul links as aforementioned. Furthermore, Moreover, macro base stations are linked to the BBU pool over the backhaul usage of the data and control interfaces, which are came from the 3GPP specifications [16], [17].

The complexity of the proposed model makes it face several types of interference, such as inter-cell interference between macro base stations, inter-tier (cross-tier) interference between macro base stations and smallcells RRHs, and inter-cell interference between smallcells RRHs.

This provided model performs Soft Frequency Reuse (SFR) technique [1], [18] for inter-cell interference mitigation between macro base stations, the cellular service region is divided into two sub-regions, each of which is operated by distinct frequency range in order to prevent cross-tier interference. Center region served by conventional macro base stations which is operate with sub-6 GHz frequency band [3], and Edge area served by RRHs, which operates with mmWave frequency band. Thus, this model targets the entire cell area; which enhances the performance in terms of cell coverage and user throughput and interference mitigation, as shown in Fig. 1. While the inter-cell interference between mmWave smallcells RRHs will be mitigated in the proposed algorithm in a section IV.

B. CHANNEL AND PATH LOSS MODEL

This paper considers a channel model suitable for a two-tier downlink heterogeneous wireless network. This model takes into account the characteristics of mmWave frequencies, making it versatile for use in different 5G network scenarios, which is important for improving the coverage and capacity of mmWave systems. It includes two sub-models [14]: a UMa channel model for macro base stations hexagonal grid with an antenna in the center of each macro base station, operate in sub-6GHz which represents the first tier of network. The second type of channel is a UMi - Street Canyon for small mmWave RRHs, which represents the second tier of network that overlaid over each macro base station to cover the cellular edge region which are appropriate for the HC-RAN system described. While users are distributed using uniform random distribution across network. Users close to cell boundaries experience boundary effects, represented by interference between mmWave small cells [19].

In the first tier of macrocells, with the exception of the MBS cell that served the user k, there is inter-cell interference power received by the same user from all other MBS cells, and the signal-to-interference plus noise ratio (SINR) is represented in the following equation [1], [3]:

$$SINR_{k_m} = \frac{P_m.G_{k_{m_i}}}{\sum_{j\in M, j\neq i} P_m.G_{k_{m_j}} + \sigma_m^2} \tag{1}$$

where σ_m^2 is the noise power, P_m is the downlink transmit powers of MBSs, and $G_{k_{m_j}}$ is a composite channel gain, which composed of path loss and channel fading and is given as follows:

$$G_{k_{m_i}} = g_{m_i} s_{m_i} l_{m_i} PL_m^{-1}(d_m) \tag{2}$$

where g_{m_i} is the antenna gain of MBS, s_{m_i} is the small scale channel fading, which is imposed to be Rayleigh random variable, l_{m_i} is the large scale channel fading, which is imposed to be a lognormal shadowing [20], and $PL_m(d_m)$ denote the UMa path loss for k user connecting to a MBS from 3GPP TR 38.901 [14], given for both LOS and NLOS case as follow:

$$PL_{mLOS}(d_m) = \begin{cases} PL_{m1}, & for\, 10\ m \le d_{em} \le d_{BPm} \\ PL_{m2}, & for\ d_{BPm} \le d_{em} \le 5\ km \end{cases} \tag{3}$$

$$PL_{mNLOS}(d_m) = max\left(PL_{mLos}(d_m), P\grave{L}_m(d_m)\right), \quad for\, 10\ m \le d_{em} \le 5\ k \tag{4}$$

where:

$$PL_{m1} = 28 + 20\ log_{10}(f_{cm}) + 22\ log_{10}(d_m) \tag{5}$$

$$PL_{m2} = 28 + 20\ log_{10}(f_{cm}) + 40\ log_{10}(d_m) - 0.6\ log_{10}(h_k - 1.5) \tag{6}$$

$$P\grave{L}_m(d_m) = 13.54 + 20\ log_{10}(f_{cm}) + 39.08\ log_{10}(d_m) - 0.6\ log_{10}(h_k - 1.5) \tag{7}$$

$$d_m = \sqrt{d_{em}^2 + (h_{MBS} - h_k)^2} \tag{8}$$

where d_m and d_{em} are the 3 slope distance and Euclidian distance between serving MBS and user, respectively. d_{BPm} is Breakpoint distance, given as:

$$d_{BPm} = \frac{4h'_{MBS} h'_k f_{cm}}{c} \tag{9}$$

where f_{cm} the carrier frequency of MBSs and c is the speed of light, $h'_{MBS} = h_{MBS} - h_E$, and $h'_k = h_k - h_E$, are the effective antenna heights at the MBS and the user, respectively, h_{MBS} and h_k are the actual antenna heights, and h_E is the effective environment height.

$\sum_{j\in M, j\neq i} P_m.G_{k_{m_j}}$ stands for, with the exception of the serving MBS cell, the inter-cell interference power received from all other MBS cells.

In the second tier of smallcells, Since the coverage of mmWave is limited due to high path loss and blockage. This dense deployment of smallcells or RRHs may result an inter cell interference received from all other RRHs, with the exception of the RRH that served the user k, and the signal-to-interference plus noise ratio (SINR) for the user k is represent in the following equation [1], [3]:

$$SINR_{k_r} = \frac{P_r.G_{k_{r_i}}}{\sum_{j\in R, j\neq i} P_r.G_{k_{r_j}} + \sigma_r^2} \tag{10}$$

where σ_r^2 is the noise power, P_r is the down link transmit powers of RRH_{r_i} and $G_{k_{r_i}}$ is a composite channel gain which composed of path loss and channel fading and is given as follows:

$$G_{k_{r_i}} = g_{r_i} s_{r_i} l_{r_i} PL_r^{-1}(d_r) \tag{11}$$

where g_{r_i} is the antenna gain of RRH, s_{r_i} is the small scale channel fading, which is imposed to be a Nakagami with normalized gamma distribution, l_{r_i} is the large scale channel fading, which is imposed to be a lognormal shadowing [20], and $PL_r(d_r)$ denote the UMi-street canyon path loss for user k connecting to a RRH from 3GPP TR 38.901 [14], given for both LOS and NLOS case as follow:

$$PL_{rLOS}\left(\mathrm{d}_r\right) = \begin{cases} PL_{r1}, & for\, 10\; m \leq d_{er} \leq d_{BPm} \\ PL_{r2}, & for\; d_{BPm} \leq d_{er} \leq 5\; km \end{cases} \tag{12}$$

$$PL_{rNLOS}\left(d_r\right) = max\left(PL_{rLos}\left(d_r\right), P\,L_r'\left(d_r\right)\right), \quad for\, 10\; m \leq d_{er} \leq 5\; km \tag{13}$$

where:

$$PL_{r1} = 32.4 + 20\, log_{10}\left(f_{cr}\right) + 31.9\, log_{10}\left(d_r\right) \tag{14}$$

$$PL_{r2} = 32.4 + 20\, log_{10}\left(f_{cr}\right) + 40\, log_{10}\left(d_r\right) - 9.5\, log_{10}\left(d_{BPT}^2 + \left(h_{RRH} - h_k\right)^2\right) \tag{15}$$

$$PL_r'\left(d_r\right) = 22.4 + 21.3\, log_{10}\left(f_{cr}\right) + 35.3 \log_{10}\left(d_r\right) - 0.3\, log_{10}\left(h_k - 1.5\right) \tag{16}$$

$$d_r = \sqrt{d_{er}^2 + \left(h_{RRH} - h_k\right)^2} \tag{17}$$

where d_r and d_{er} are the 3 slope distance and Euclidian distance between serving RRH and user, respectively. d_{BPr} is Breakpoint distance, given as:

$$d_{BPr} = \frac{4h'_{RRH} h'_k f_{cr}}{c} \tag{18}$$

where f_{cr} is the carrier frequency of mmWave RRHs and c is the speed of light, $h'_{RRH} = h_{RRH} - h_E$, and $h'_k = h_U - h_E$, are the effective antenna heights at the RRH and the user, respectively, h_{RRH} is the actual antenna heights.

$\sum_{j\in R, j\neq i} P_r.G_{k_{r_j}}$ stands for, with the exception of the serving RRH, the inter-cell interference power received from all other RRHs.

IV. OPTIMIZATION PROBLEM FORMULATION

Due to each tier operates at a different frequency band, as illustrated by the above equations (1) and (10), the suggested system avoids inter-tier interference, also it does not have inter-cell-interference between macrocells in the first tier because to the use of (SFR) technique as mentioned above in section III. In this case the interference comes from the second-tier between mmWave RRHs.

Assumptions: The BBU controller, located within the BBU pool, maintains comprehensive information about the network. This information is regularly updated using reports from users via the associated RRHs. The controller has access to the location coordinates and coverage areas of all RRHs. It is responsible for executing algorithms that manage handover and association decisions, which are subsequently communicated to the RRHs.

Suppose there are K number of active users and R number of RRHs. also assume there are S number of BBUs, where S is equal to the number of RRHs R at most. Each active user k in the network is equipped with a single-antenna device, which means each user can be associated with only one RRH r at most in the network at a particular time t. Users move in the network using random-walk mobility model. The user is assumed to be equipped with a location service (e.g., GPS), and when a certain condition is met, the user reports its information to the serving RRH. Additionally, each RRH r can be associated with one BBU s at most. All the RRHs are connected to the BBU pool by a fronthaul link. The BBU pool controls the User-RRH association with information received from users each time.

The average throughput of a user, denoted by T, is adapt on resource availability and, as a result, is dependent on resource allocation among users attached to the same BBU in the network. Hence, assuming a full traffic model and a fair model of resource sharing, the average throughput attained by user k, who is associated to RRH r and allocated to BBU s, can be expressed as follows [12]:

$$T = \frac{T_{k,r,s}}{k_s} \tag{19}$$

where $T_{k,r,s}$ is the peak user throughput which is calculated by the Shannon formula:

$$T_{k,r,s} = W_r \log_2\left(1 + SINR_{k,r,s}\right) \tag{20}$$

and k_s represents how many users there are sharing the BBU s radio resource, and as follows:

$$k_s = \sum\nolimits_{r\in R} \sum\nolimits_{u\in U} X_{k,r} Y_{r,s} \tag{21}$$

The optimization problem (P) objectives to mitigate inter-RRHs interference by finding the user k associated with best RRH r, allocated to BBU s, this maximize the overall user throughput in the network which based on equations (19), (20), was formulated as follows:

$$\max\left(\mathrm{P}\right) = \sum\nolimits_{s\in S} \sum\nolimits_{r\in R} \sum\nolimits_{k\in K} X_{k,r} Y_{r,s} T \tag{22}$$

where $X_{k,r}$ the complexity to determine which user association solution is the best, and $Y_{r,s}$ the complexity to determine which RRH clustering solution is the best.

Subject to constraints:

$$\sum\nolimits_{r\in R} X_{k,r} \leq 1, \quad \forall k \in K \tag{23}$$

$$\sum\nolimits_{s\in S} Y_{r,s} \leq 1, \quad \forall r \in R \tag{24}$$

$$X_{k,r} \leq t_r, \quad \forall r \in K \times R \tag{25}$$

$$Y_{r,s} \leq t_s, \quad \forall s \in R \times S \tag{26}$$

$$X_{k,r}, Y_{r,s}, t_r, t_s \in \{0, 1\}, \quad \forall (k, r, s) \tag{27}$$

Constraint (23) indicate that every user k can at most be associated to a single RRH r. Constraint (24) indicate that every RRH r can at most be attached to a single BBU s. Constraint (25) show that RRH r is only activated when it is linked with one user k at least. Constraint (26) show that BBU s is only activated when it is attached to one RRH r at least. Constraint (27) denote that all the variables, $X_{k,r}$, $Y_{r,s}$, t_r, t_s are binary decisions.

Due to the large path loss gap between LOS and NLOS links, we adopted a joint User-RRH association and RRH-BBU clustering strategy suitable for mmWave communications in 5G HC-RAN network to eliminate inter-RRHs interference in a way that maximizes the overall throughput of the network achieved by the user and manage resource consumption. In order to solve the joint problem despite its complexity, we suggest formulate the joint optimization problem as a mixed-integer non-linear programming problem by breaking down the joint problem into 2 sub-problems: The User-RRH association and the RRH-BBU clustering, to reach stable and jointly efficient solutions.

The User-RRH association sub-problem is solved first by Heuristic Algorithm adopting the strategy of selecting R RRHs based on minimum path losses to determine the links between the user and the RRH. yields a decision of association for each user, and each user is then notified of this decision. Eventually, each user integrates the decision made by RRH with its list of priority and notifies selected RRH.

Then, taking into account the outputs of the User-RRH association sub-problem and, the RRH-BBU clustering sub-problem gets solved by proposing an adaptive custom k-mean clustering algorithm with additional features such as equalizing cluster sizes for achieve a fair resource sharing, realigning centroids, and splitting clusters. The problem of mapping determines the association between RRHs and BBU. Specifically, according to the merge-and-split principles, where the RRHs are organized into independent and disjoint equal clusters, and this is iterated until convergence or until a maximum number of iterations is reached. The merging and splitting procedures are performed within each iteration until no more merge and-split can be further done, then updates centroids based on the mean of assigned data points (RRHs Positions) and assigns them to the nearest centroid.

The best clustering solutions are identified by evaluating the load balancing across BBUs and minimizing the total load imbalance. This is achieved by considering the number of users associated with each RRH-BBU cluster and ensuring that each BBU is adequately utilized without exceeding its capacity. The clustering solution that best distributes the users across BBUs, minimizing load variance and ensuring each BBU operates within capacity constraints, is selected. In addition to load balancing, the clustering solution is evaluated based on its ability to maximize the network throughput and improve coverage for users. These factors are reflected in the clustering cost function, which accounts for the number of users served, PRB utilization, and the overall network performance in terms of throughput and coverage.

The User-RRH association sub-problem gets solved first to eliminate inter-RRHs interference in a way that maximizes the overall throughput of the system achieved by the user. and by taking into account the outputs of the User-RRH association sub-problem, Then, the RRH-BBU mapping sub-problem gets to manage resource consumption.

The best solutions in the optimization loop are determined by maximizing user throughput while ensuring that the system constraints are met. This involves solving the user-to-RRH association matrix by selecting the RRH that provides the highest SINR to each user, ensuring that BBUs are not overloaded. The solution is considered "best" when it maximizes the average user throughput, subject to constraints such as the number of available PRBs per BBU, active BBUs, and network coverage requirements. We aim to find the solution that delivers the highest throughput to users while minimizing the number of active BBUs to conserve resources.

The associations and clusterings that are formed lead to efficient joint solutions and are repeated until convergence is reached. The number of iterations for convergence can vary depending on several factors, such as the initial conditions of the network, the size of the network (the number of users, the number of RRHs), the specific initial configurations, and the configuration of the optimization parameters, including the number of observations, the initial cluster assignment, and whether the flags for realign cluster positions are enabled. for simplicity, all of the above are illustrated in pseudo-code in **Algorithm 1**.

When analyzing the computational complexity, consider the major components and their associated operations:

- **User-RRH Association:** Complexity $O(K \times R)$, where K is the number of users, R is the number of RRHs, reflects the operation of associating users with RRHs. This does not inherently include the BBU clustering, but rather focuses solely on the relationship between users and RRHs. In this process, for each user (K), a decision is made with respect to all RRHs (R), leading to the product of operations.
- **RRH-BBU clustering (K-Means Clustering)**: Complexity $O(I \times R \times S)$, where I is the number of iterations, R is the number of RRHs, and S is the number of BBUs. The RRH-BBU association is not performed iteratively for each RRH, already encompasses the process of associating RRHs with BBUs. This means that in each iteration of the clustering algorithm, all RRHs are simultaneously reassigned to the nearest BBU based on the current cluster centroids. This process is repeated until convergence, rather than iterating over each RRH individually, reflecting the simultaneous assignment of RRHs to BBUs in each iteration of the algorithm. The algorithm does not perform a sequential iteration over

individual RRHs but rather updates the association for all RRHs in parallel within each iteration.

Algorithm 1 Adaptive Joint Approach for the User-RRH Association and RRH-BBU Clustering

1: Initialize Parameters:
Users and RRHs positions, path loss values, SINR values
2: Iterative Process:
3: User-RRH Association: solve sub problem using Heuristic approach
-Assign user k to the RRH r based on minimum path loss criterion
- Update X_kr (k, r) = 1
4: repeat
5. RRH-BBU clustering: solve sub problem using k-mean clustering
-Assign RRH r to the BBU s based on actual load in the network criterions and X_kr (k, r) solution
- Update Y_rs (r, s) = 1
6: Repeat:
7: Re-associate users according to the new RRH-BBU clustering
8: Until No more User-RRH Association and RRH-BBU clustering need to be modified.
9:End

By considering the combined operations, the total complexity of the proposed joint algorithm, considering the loops over different variables, including users, RRHs, BBUs, and iterations, can be processed in $O\,(K \times R + I \times R \times S)$, Here, the variables represent the numbers of users, RRHs, BBUs, and K-means iterations. This Big "O" notation captures how the computational effort scales with the number of users (K), RRHs (R), BBUs (S), and other simulation parameters. As the network size increases, particularly with more users and RRHs, the computational load will grow significantly, particularly due to the association and clustering steps.

Thus, the user-RRH association step and the RRH-BBU clustering step are generally distinct. The RRH-BBU association is not typically performed iteratively within each RRH but is rather clustered as a separate process.

All of the above for joint optimization method are illustrated in the Fig.2.

V. PERFORMANCE METRICS

A. THE COVERAGE PROBABILITY

This system assumed open access, which is unrestricted meaning that user can associate with any tier of MBS or mmWave RRH without any limitations [21]. However, Positive power biasing and minimum pathloss are utilized to move more edge users from the MBS tier to the mmWave RRH since MBS transmit at a higher power than mmWave RRHs. For example, a User would associate with a mmWave RRH if:

$$P_r g_r B_r PL^{-1}_{min,r}(d_r) > P_m g_m B_m PL^{-1}_{min,m}(d_m)$$

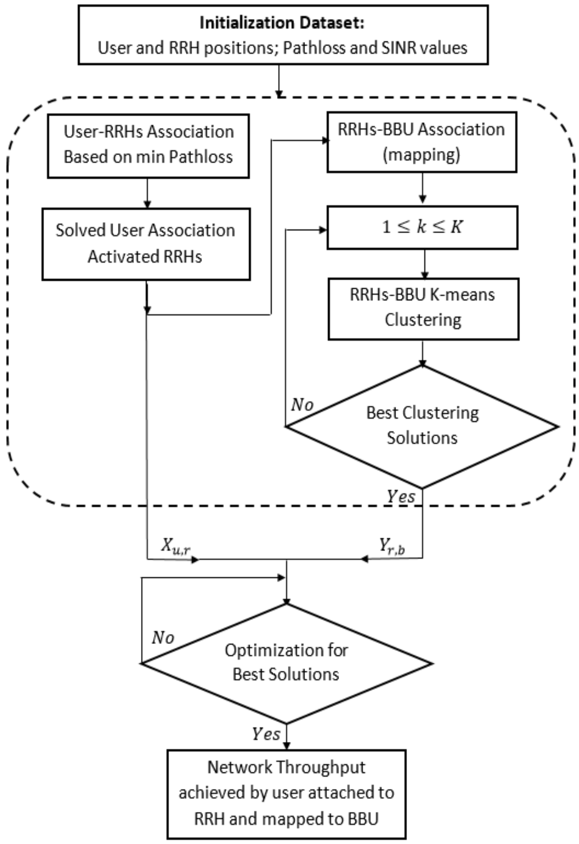


FIGURE 2. Flow chart of the optimization method.

Furthermore, if not, a user would associate to an MBS. Where $PL^{-1}_{min,m}(d)$, $PL^{-1}_{min,r}(d)$ stand for the minimum path losses of user linking to the MBS, and RRH respectively, and B_m, B_r serves as a user association biasing factor with MBS, and RRH respectively. Based on maximum received biased power, user connected to the MBS in the cell center region have B_m = 0dB, while $B_r > 0$ is for user connected to a mmWave RRH and located in the cellular edge region.

The coverage probability is presented in a scenario where users are randomly located in network coverage, where each user connects to a defined cell, if their SINR is above a predefined target threshold SINR ($\mathcal{T}_c$).

$$P_{SINR}(\mathcal{T}_c) = P(SINR > \mathcal{T}_c) \tag{28}$$

The SINR coverage probability (P_{SINR_k}) of the proposed system can be represented by the following expression [1], [21]:

$$\begin{aligned} P_{SINR_k}(\mathcal{T}_c) &= \mathcal{A}_m P_{SINR_{km}}(\mathcal{T}_c) + \mathcal{A}_r P_{SINR_{kr}}(\mathcal{T}_c) \\ &= \Big(\bigcup\nolimits_{j\in\{m,r\}} \mathcal{A}_j P(SINR_{kj} > \mathcal{T}_c)\Big) \end{aligned} \tag{29}$$

where $\mathcal{A}_m$ and $\mathcal{A}_r$: are the association probabilities of mmWave and sub-6Ghz, respectively, and $\mathcal{A}_{j\in\{m,r\}}$ is the association probability, which is depends on users' association to the MBS or mmWave RRH.

B. THE RATE COVERAGE PROBABILITY

The achievable rate by user can be given as:

$$\mathcal{R}\left(K_j\right) = \log_2\left(1 + SINR_{k_j}\right), \quad j \in \{m, r\} \tag{30}$$

The rate coverage probability in an open access system is presented when users are considered to be within rate coverage in the network, if their downlink rate is above a predefined target threshold rate (ρ_r). So the Rate Coverage Probability is given by:

$$\mathcal{R}(\rho_r) = P(\mathcal{R} > \rho_r) \tag{31}$$

So the rate coverage probability $\mathcal{R}(\rho_r)$ of the proposed system is represented by the following expression [1]:

$$\begin{aligned}\mathcal{R}\left(\rho_r\right) &= \left(\bigcup_{j\in\{m,r\}} \mathcal{A}_j P\left(log_2\left(1 + SINR_{k_j}\right) > \rho_r\right)\right)\\ &= \left(\bigcup_{j\in\{m,r\}} \mathcal{A}_j P\left(SINR_{k_j} > (2^{\rho_r} - 1)\right)\right)\end{aligned} \tag{32}$$

VI. SIMULATION IMPLEMENTATION

Simulation results for the proposed system's architecture are obtained using MATLAB, while the analysis with 100 iterations is conducted to evaluate system performance. The power levels, path loss models, and other channel parameters used in the simulation are sourced from the 3GPP TR 38.901 specifications [14], ensuring that the simulation environment reflects realistic conditions for 5G networks. Various metrics are calculated based on the simulation parameters outlined in TABLE 1.

The joint optimization problem is formulated as a mixed-integer non-linear programming problem and successfully decomposes it into two sub-problems for efficient solutions, and to demonstrates the effectiveness of the proposed solutions through simulation results, showcasing improved network utility and it performance. For the proposed first sub-problem of User-RRH association, while maximizing throughput is it's the primary objective, its solution is verified and its results are compared with the limited capacity User-RRH association algorithm (LC UA) and applied to all proposed deployment scenarios. On other hand, the objective of the second sub-problem of RRH-BBU k-means clustering is to manage the resources in the network by clustering RRHs with BBUs into clusters in the BBU pool controller, which is one of the working principles of C-RAN, depending on actual load and number of active RRHs in the network to find K RRH-BBU clusters, which manage and reduce resource consumption, in light of this, to prove the effectiveness of the proposed joint algorithm in maximizing throughput and resource management, it was applied to three types of clustering:

- One-to-One clustering or the common name "no clustering"
- Many to one clustering
- One clustered configuration

TABLE 1. Simulation parameters.

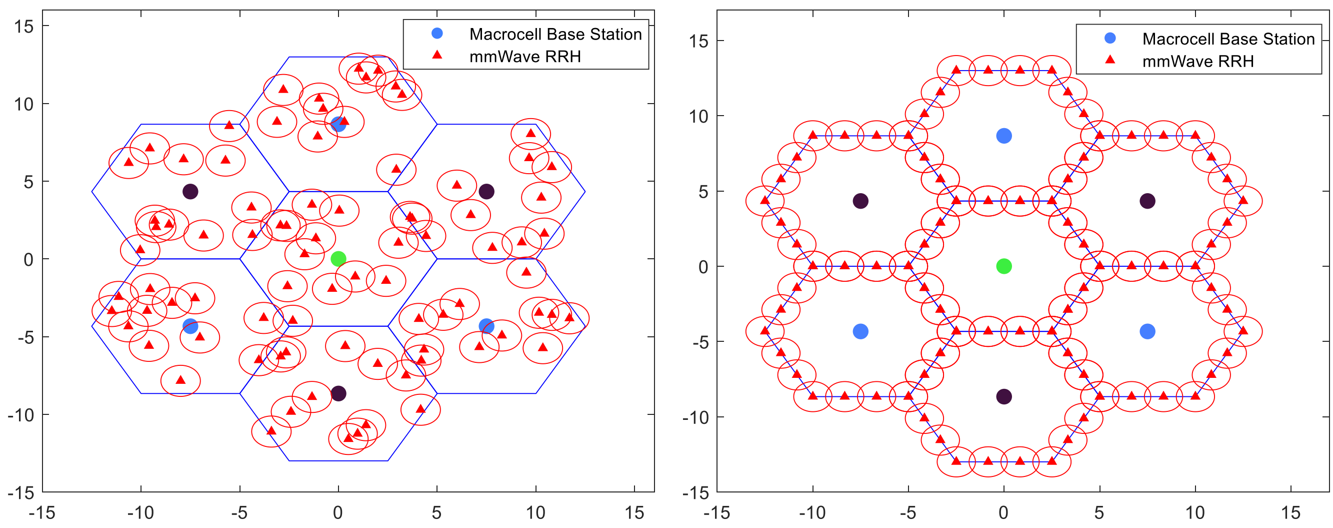
Parameter	Value
Network architecture	Two tier Hexagonal HC-RAN network
No. of macrocells	7
No. of smallcells (RRHs)	84
Radius of macrocells	500 meters
Radius of smallcells	150 meters
Macrocells' carrier frequency	2 GHz
smallcells' carrier frequency	28 GHz
No. of Users	Vary from 70 to 2000
Macrocells bandwidth (W_m)	20 MHz
Smallcells bandwidth (W_r)	1 GHz
noise power (σ_m^2)for sub-6 GHz[3]	$-174\ dBm/Hz + 10\log(W_m) + 10$dB
Noise power (σ_r^2)for mmWave[3]	$-174\ dBm/Hz + 10\log(W_r) + 10$dB
Shadow fading for Uma for LOS and NLOS	4dB 6dB
Shadow fading for UMi for LOS and NLOS	4dB 7.82dB
down link transmit powers of RRH_r (P_m)	30 dBm
down link transmit powers of MBSs (P_m)	46 dBm

VII. RESULTS AND DISCUSSION

A. SINR COVERAGE PROBABILITY ANALYSIS

Figure 4 illustrates the SINR coverage probability performance relative to the SINR threshold to evaluate the performance of the proposed systems. This assessment is carried out in scenarios where mmWave smallcells are either deployed randomly or positioned at the edges of macrocells (c.f. Fig. 3), considering both LOS and NLOS cases. The comparison was performed for the same number of RRHs when there are 140 users under the same network conditions for all scenarios.

In the LOS case, both deployment scenarios, random and on edge, exhibit higher coverage probabilities across most



(a) (b)

FIGURE 3. Comparison scenarios (a) for(a) Random RRHs deployment, (b) on edge RRHs deployment.

SINR thresholds than their NLOS counterparts, by slight roughly 6.1% and 7.5 %, respectively. This is expected since LOS conditions generally offer a clearer signal path, leading to stronger and more reliable signal strength. Conversely, NLOS scenarios show a notable decrease in coverage probabilities as the SINR threshold rises. The results showing only a small performance degradation in SINR coverage probability and rate coverage probability between the NLOS and LOS scenarios may seem counterintuitive, given the typically more challenging conditions in NLOS environments. This suggests that the proposed system is well-functioning, interference management is effective, and power usage is efficient. These improvements mitigate the negative effects of NLOS conditions, reducing the performance gap between LOS and NLOS scenarios. In addition, the deployment of mmWave smallcells in the network affects the performance difference between LOS and NLOS scenarios. If users in NLOS conditions are closer to the base stations or small cells that serve them, the increased path loss can be somewhat compensated by proximity, resulting in a smaller difference in performance metrics. NLOS scenarios experience a significant drop in coverage probabilities as the SINR threshold increases, with performance degrading more gradually compared to the sharp declines seen in LOS scenarios at high thresholds. This gradual decline is due to obstacles and multipath fading in NLOS environments. For both LOS and NLOS conditions, increasing the SINR threshold from 0dB to 30dB results in a steeper decline in coverage probability, highlighting the difficulty of maintaining higher SINR levels in urban or cluttered environments with significant signal attenuation or interference.

The general trend in deployment scenarios for both LOS and NLOS conditions indicates that the probability of coverage converges at the highest SINR threshold values for all scenarios. As the SINR threshold increases from 0dB to 30dB, there is a steeper decline in coverage probability, underscoring the challenge of maintaining higher SINR levels in urban or cluttered environments with significant signal attenuation or interference. At higher SINR thresholds, notable differences emerge between scenarios. Specifically, random deployments tend to outperform edge deployments at higher SINR thresholds by approximately 23.99% and 25.63%, respectively. This improved performance can be attributed to optimized signal paths when using the minimum path loss for user association with RRH and potentially reduced interference. This could be attributed to optimized signal paths when relying on the minimum path

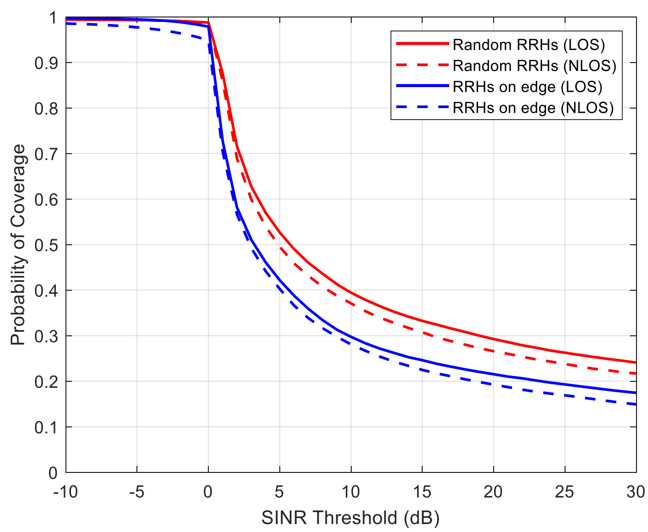


FIGURE 4. SINR coverage probability when140 users connected to the network for different scenarios.

loss for user association with RRH and potentially reduced interference.

The results underscore the importance of strategic deployment of cell sites (RRHs), whether at the edge or randomly distributed, and accounting for LOS and NLOS conditions in network design. This is crucial for network planning to enhance SINR coverage probabilities, particularly when aiming to meet elevated quality of service standards, while in the case of on edge deployment, which shows lower coverage probabilities, network improvements such as the use of repeaters, advanced technologies, and beamforming might be required to boost the signal quality and coverage.

B. RATE COVERAGE PROBABILITY

Figure 5 illustrates the rate coverage probability across different deployment scenarios, related to the rate threshold of the proposed systems. The comparison was also conducted under the same network conditions and with the same number of RRHs while serving 140 users across all scenarios.

All scenarios start with high coverage probabilities near or at 1 when the rate threshold is zero, indicating that almost all cells can provide minimal rates. As the rate threshold increases, the probability that a cell can meet this rate drops, which is expected as higher data rates are more challenging to sustain over different locations and conditions within the network. Both Random and on-edge deployment scenarios show slightly higher coverage probabilities in LOS conditions compared to NLOS. LOS consistently outperforms NLOS across all rate thresholds, with average gains of 2% and 9%, respectively. This is because LOS environments typically encounter fewer physical obstructions, resulting in stronger and more reliable signal propagation.

Despite being more challenging, NLOS conditions demonstrate commendable robustness, suggesting these configurations might be more suitable for environments with physical obstructions or varied terrain. Random RRH deployments are more effective at meeting higher rate demands in both LOS and NLOS conditions, with average gains of 41% and 51% in rate coverage probability compared to on-edge RRH deployments. This suggests that on edge RRHs deployment generally provide the lowest coverage across various rate thresholds.

The observations highlight that different cell deployment strategies, particularly in LOS and NLOS conditions, significantly impact network performance. Random RRH deployments are more effective than edge deployments, providing better rate coverage probability and adapting to real-world challenges like obstacles, user distribution, and interference. This insight can guide network design improvements, emphasizing the importance of optimizing resource use based on actual data traffic demands rather than purely geometric considerations. Thus, while edge deployments might initially seem efficient or strategically simple, they often fail to address the complex, varied demands of real-world environments where obstacles, user distribution, and interference patterns create a more dynamic challenge.

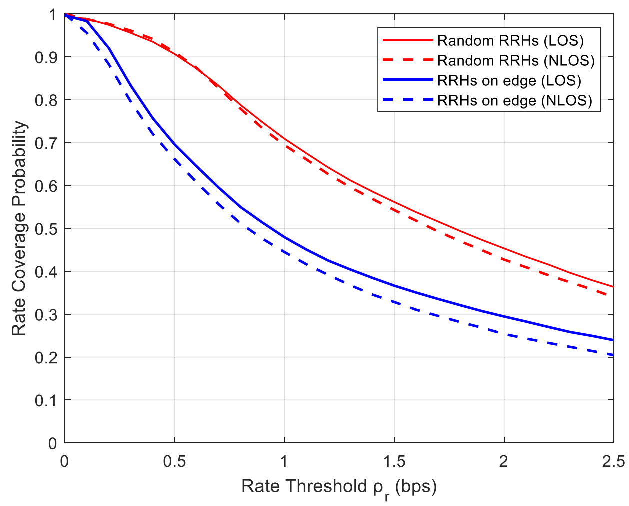


FIGURE 5. Rate coverage probability when140 users connected to the network for different scenarios.

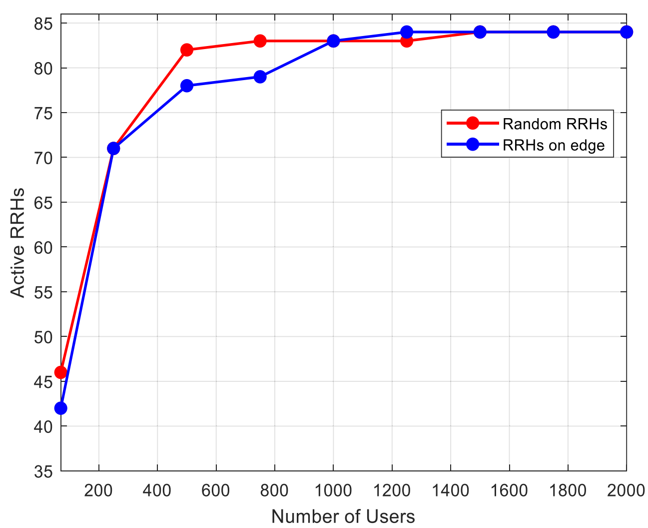
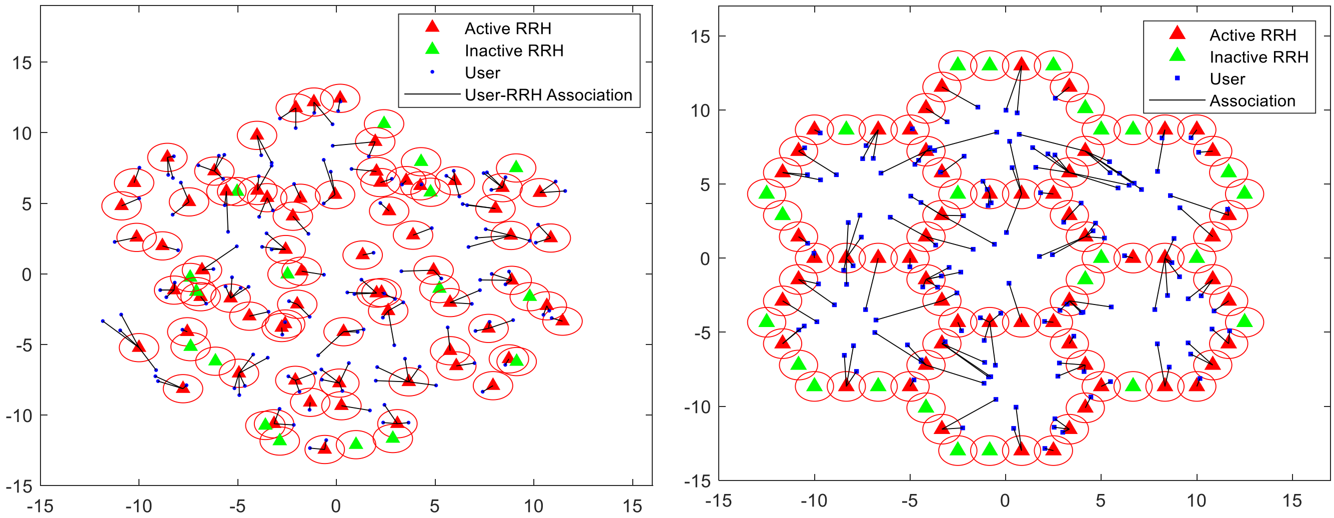


FIGURE 6. The number of active RRHs.

C. JOINT USER ASSOCIATION AND RRHS K-MEAN CLUSTERING OPTIMIZATION

1) USER ASSOCIATION SOLUTION

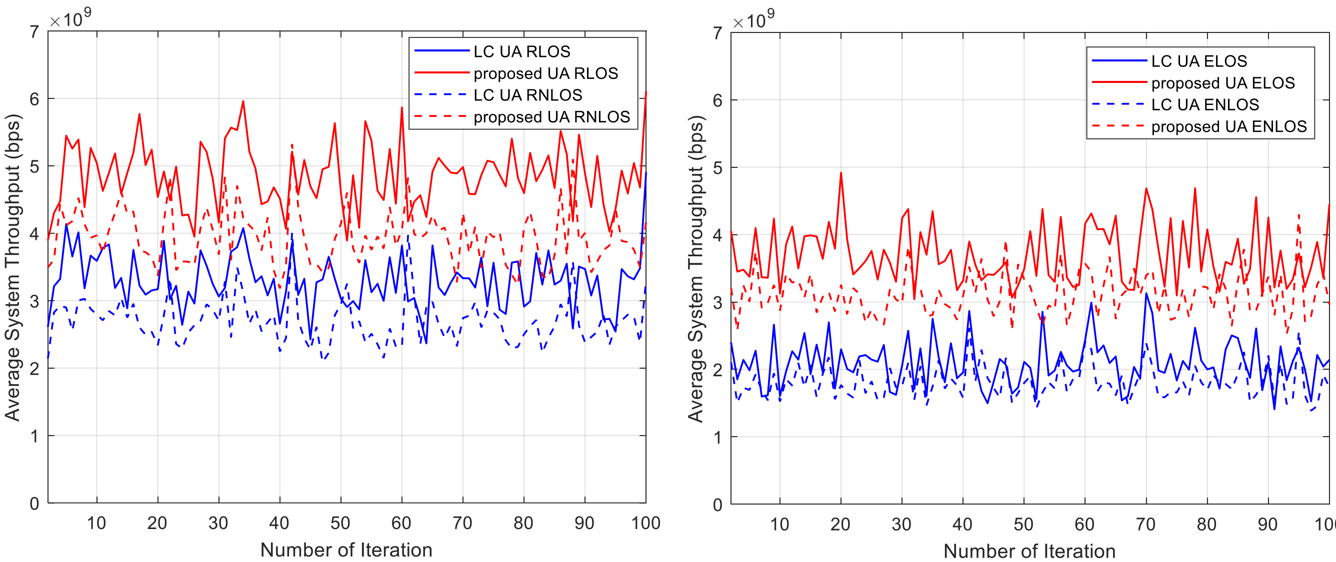
Figure 6 displays the number of active RRHs versus the number of users for both deployment strategies (random and on edge) when applying the proposed algorithm for user association with RRH solution. There is an increasing trend in the number of users and active RRHs for both deployment strategies. This indicates that more active RRHs are needed to serve more users effectively. Both strategies eventually saturate with the total number of RRHs deployed when the number of users increases significantly. Random RRHs deployment reaches saturation quicker than on-edge deployment with fewer users, which means it's potentially operating at full capacity sooner. This can be beneficial where high user density is expected. might provide better connectivity with a rapid increase in user density, as it can activate more RRHs



(a)

(b)

FIGURE 7. User association with active RRHs for(a) Random RRHs deployment, (b) on edge RRHs deployment.



(a)

(b)

FIGURE 8. Average network throughput for User-RRH association solution sub problem for (a) Random RRHs deployment, (b) on edge RRHs deployment.

quickly, while the on edge deployment reaches saturation more gradually and does not completely saturate until there are higher numbers of users, maintaining a reserve capacity that might be beneficial under varying load conditions. might experience less congestion per RRH initially due to the slower increase, possibly providing more consistent service quality over a wide range of user counts.

Random RRHs deployment might consume more resources initially due to a large number of RRHs being active earlier. This could mean higher energy consumption and, possibly, higher maintenance costs. while in the on edge deployment by increasing the active RRHs more gradually might be more efficient in terms of energy usage per RRH in lower user scenarios, but might require more infrastructure to ensure all users are well-served as the number grows.

Figure 7 shows the effectiveness of user association solution with RRHs in reducing interference for both scenarios, as each user is associated with at most one RRH, which leads to its activation and appears in red, while the inactive RRH appears in green because it is not associated with any user. In summary, for users' association the choice between random and edge RRHs deployment should consider the

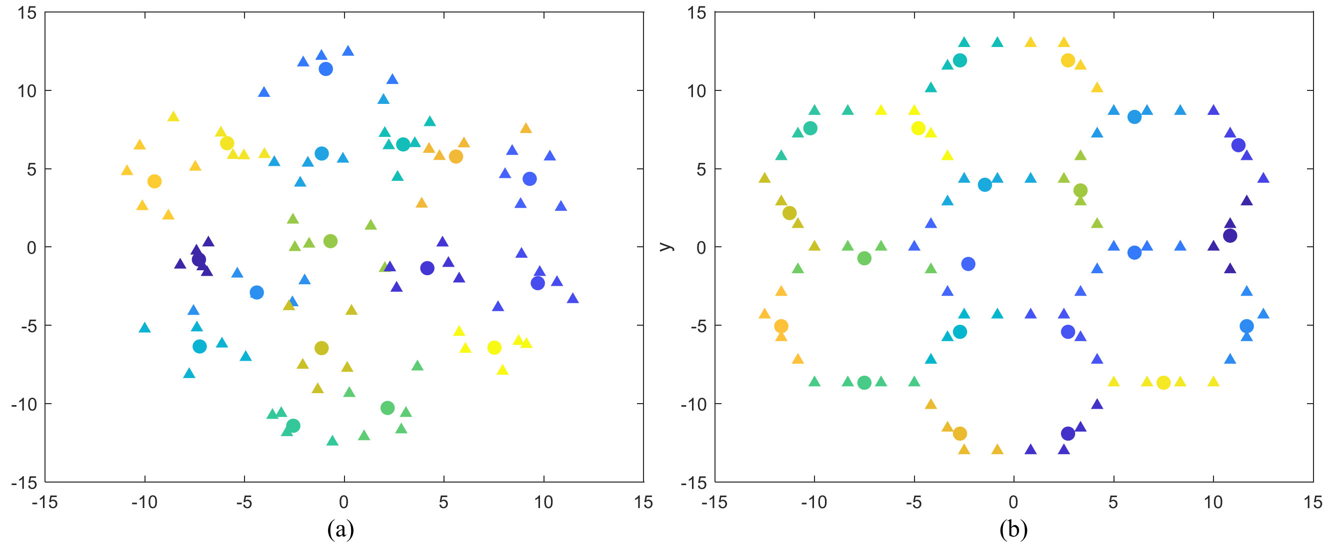


FIGURE 9. RRHs K-mean clustering for (a) Random RRHs deployment, (b) on edge RRHs deployment.

expected user distribution and density, the desired quality of service, and resource management efficiency. Edge deployment might be preferable in scenarios where user load increases predictably, whereas random deployment might be better suited to areas with sudden peaks in user density.

Figure 8 displays the average network throughput versus the number of Iteration for both deployment strategies for the proposed User-RRH association solution based on minimum path loss as a basic criterion compared with Limited Capacity User-RRH Association algorithm (LC UA). This is done before applying RRH-BBU Clustering sub problem solution. It observed that the proposed sub problem solution outperforms the CL UA in both the random and edge deployment scenarios by approximately 38% and 27%, respectively. The random deployment scenario also outperforms the edge deployment by 29%.

In the provided implementation, for the User-RRH Association, typically, the optimization loop converges within 50 to 100 iterations. The convergence behavior is influenced by the dynamic nature of the path loss and SINR calculations, which vary depending on user and RRH positions and interference levels.

In most cases, convergence is observed around 75 iterations when there are moderate numbers of users and RRHs. For larger, more complex scenarios, the algorithm may require up to 100 iterations, especially if higher levels of interference or more significant path loss variations are present.

2) RRHS K-MEAN CLUSTERING SOLUTION

Figure 9 shows RRHs K-mean clusters for random and on edge RRHs deployment, where the optimal k value is determined automatically based on the actual load on the network and the size of the data set (number of RRHs) to achieve clusters of the same size to ensure a fair model of

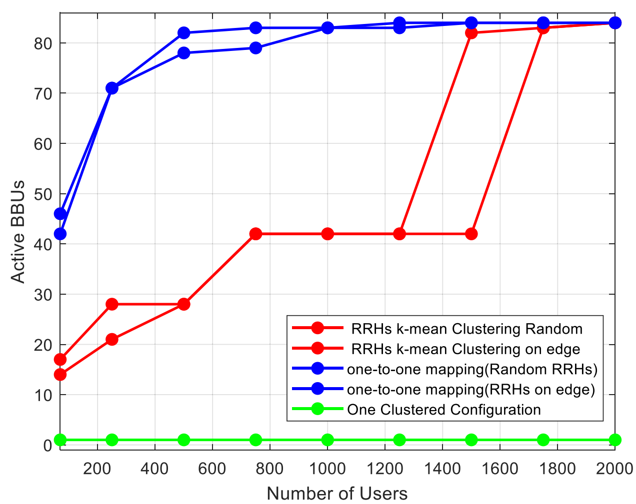


FIGURE 10. The number of active BBUs.

resource sharing. The number of active BBUs changes when the actual load on the network changes regardless of the deployment method (see Fig. 10). This is due to the network size of data set are deployed in the network, so that the BBU is activated when there is at least one active RRH in a cluster. This indicates that the proposed sub problem of RRHs K-mean clustering mechanism is efficient, as fewer number of BBUs can handle varying loads without needing additional resources. This configuration is likely optimizing the resource allocation efficiently.

In one-to-one clustering, regardless of the simple difference between random and on edge RRHs deployment, the number of active BBUs increases significantly as the number of users grows. This shows a less efficient use of BBUs, leading to a need for more active BBUs as user demand increases,

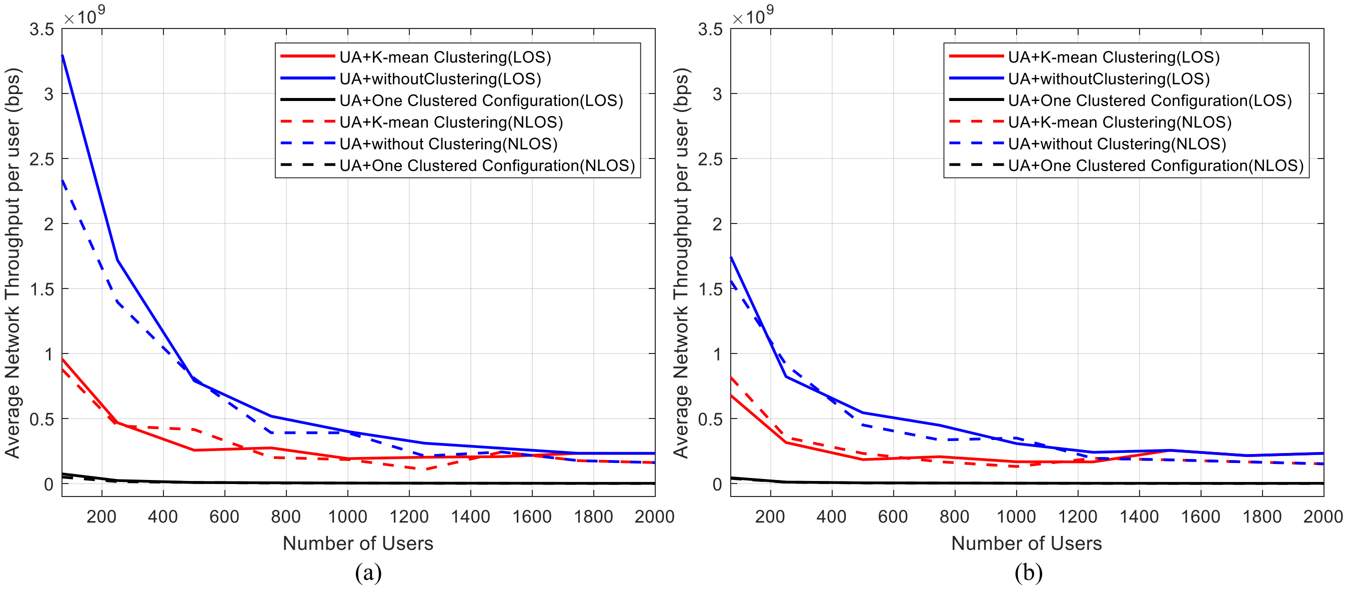


FIGURE 11. Average network throughput per user for scenarios (a) Random RRHs deployment, (b) on edge RRHs deployment.

and it lacks the efficiency seen in the RRHs K-mean clustering method in saving resource allocation when the actual load on the network is low.

In ca se of one clustered configuration maintains just one active BBU throughout all user levels and the methods of RRHs deployment, suggesting a highly optimized or theoretical scenario where one BBU is sufficient regardless of user load. This is either an ideal case or a scenario with very efficient resource management, possibly involving advanced techniques like virtualization or significant sharing of resources as shown in Fig. 10. Overall, RRHs K-mean Clustering appears to balance efficiency and capacity well compared to other methods of clustering. This approach not only improves the quality of service provided to users but also enhances the operational efficiency of the entire network, particularly in handling higher user densities without increasing the number of active BBUs. The grand coalition scenario, while showing minimal BBU use, may be overly optimistic or based on assumptions that might not hold in practical deployments.

In the provided implementation, for applying the K-means clustering algorithm, the optimization loop typically converges within 15 to 50 iterations. This variation is primarily due to the dynamic adjustment of the splitting parameters and the realignment process that occurs when there are an equal number of observations per cluster. The algorithm dynamically increases the split factor after a set number of iterations, allowing the clusters to split or merge as needed to ensure convergence. This contributes to the flexibility in the number of iterations.

Figure 11 illustrates the average network throughput as a function of the number of users under different conditions for clustering and deployment scenarios, given as the total throughput achieved within the system over the total number of users connected to the network. The general trend in all scenarios is that average throughput decreases as the number of users increases. This behavior is consistent with the principles of network congestion, where more users share the available bandwidth, reducing individual throughput. The highest user throughput was obtained with the proposed user association scheme and one-to-one mapping for RRHs (without clustering) because the throughput achieved by the user depends on the number of available resources, and due to the availability of radio resources (number of active BBUs) the throughput is significantly higher, especially when compared to K-mean clustering methods. This indicates that allocating and managing resources becomes more difficult in one-to-one mapping in crowded networks, leading to decreased performance and scalability issues, and this is offset by increased in resource consumption. User association with K-mean clustering approach maintains relatively lower throughput than without clustering across different numbers of users in all scenarios and conditions, but the throughput of this method remains relatively stable even as the network becomes denser, which may indicate that clustering provides improvements in interference management and reduces resource consumption, despite lower throughput than without clustering. User association with one clustered configuration is the least productive in all scenarios and conditions due to the limited number of resources provided by this solution (only one BBU is activated) to support traffic load growth. This may indicate that one cluster configuration is insufficient to deal with diverse user requirements and geographical spread. As shown in Fig. 10, the number of active BBUs varies according to the traffic load on the network. As a result, it achieves lower user productivity most of the time.

In random deployment of RRHs, generally achieves the highest throughput for each user, indicating that specific clustering strategies might be more effective than on-edge deployments. This might be due to better management of the higher user density and specific geographical challenges over the whole cell area. As for LOS versus NLOS, the benefits of clustering are more pronounced in LOS scenarios, where the direct paths allow for more effective use of resources managed by clustering algorithms.

In the provided implementation, for applying the K-means clustering algorithm and user-RRH association optimization, we typically observe that the optimization loop converges in 20-30 iterations. These iterations are sufficient to stabilize the system and yield optimal results in terms of SINR and user throughput distribution. The convergence is influenced by the initialization of clusters and the realignment steps, particularly when realigning the clusters to ensure equal size distribution of RRHs among BBUs. We chose this configuration to balance computational efficiency and the quality of the results. However, if different constraints or larger-scale networks are introduced, the number of iterations may vary accordingly. In our experiments, we ensured the optimization loop converges within a reasonable number of iterations to maintain practicality for real-time network implementations.

VIII. CONCLUSION

The analysis presented in this research across different deployment scenarios under LOS and NLOS conditions and optimization strategies reveals significant insights into network performance. The strategic deployment of mmWave cell sites plays a crucial role in enhancing network coverage, rate, throughput, and resource management, as well as mitigating interference based on user association and the prudent use of clustering techniques. The analysis presented in this research across different deployment scenarios under LOS and NLOS conditions and optimization strategies reveals significant insights into network performance. The strategic deployment of mmWave cell sites plays a crucial role in enhancing network coverage, rate, and throughput, as well as mitigating interference based on user association and the prudent use of clustering techniques. The k-means RRH clustering strategies and implemented user association strategies have proven effective in enhancing network performance and quickly adapting to varying traffic loads. These clustering strategies not only efficiently manage interference but also optimize resource consumption. These strategies are particularly critical in managing the complexities of modern wireless communication environments, where maintaining a precise balance between quality of service and efficient resource management is essential, especially in high-density areas and complex urban environments. Emphasizing deployments in urban areas can be especially beneficial as LOS conditions can be maximized and NLOS challenges mitigated. Furthermore, network operators should consider robust deployment strategies and clustering algorithms, depending on the increasing density of network users and diverse environmental conditions, and the results underscore the need for dynamic and context-aware clustering strategies in managing network throughput, especially increases in user density and changes in network conditions.

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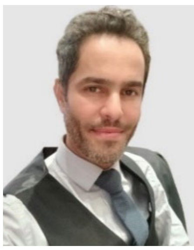

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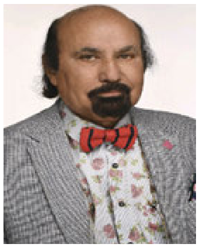

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