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# Interference Mitigation for Millimeter Wave Communications in 5G Networks Using Enhanced Q-Learning

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## ABSTRACT

Since the coverage of millimeter waves (mmWave) is limited due to high path loss and blockage, it is deployed in small cells. This dense deployment of base stations and access points resulted in significant interference. Therefore, interference mitigation is the main challenge in designing the new millimeter-wave communication technologies in the existing 5G system. Therefore, in this paper, a two-tier Heterogeneous Cloud Radio Access Network model is presented, which performs a technique inspired by soft frequency reuse (SFR) to mitigate interference. The cellular service region is divided into two sub-regions, center region is served by conventional macro base stations, which operate in the sub-6 GHz frequency band, while the edge area is served by Remote Radio Heads (RRHs), which operate in the millimeter-wave frequency band to avoid interference between tiers. User-RRH associations are introduced to mitigate interference between small RRHs and maximize network throughput using an Online Multi-Agent Q-Learning (MAQL). The proposed MAQL solution, based on the least path loss as a basic criterion for User-RRH association, outperforms in average network throughput per user a previous study based on average SINR as a basic criterion for association for two types of RRHs deployment scenarios in the heterogeneous network approximately by 66.4% and 21%, respectively, at the lowest number of users. The difference gradually decreases with the increasing user numbers until it reaches 8.7% and 9.8%, respectively. Even though the gap between throughput performance narrows as user density increases, the proposed method consistently outperforms the alternative strategy, indicating its ability to adapt and manage network resources more effectively even under higher traffic loads.

**Keywords:** Millimeter Wave (mmWave), Heterogeneous Cloud-Radio Access Network (HC-RAN), User-RRH Association.

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## 1. NTRODUCTION

The fast progress of communication technologies, in the latest years, has influenced significant hurdles in 5G networks. These hurdles come from the rise in mobile data usage due to the adoption of various personal computing devices like laptops, smartphones, and smart wearables along with a multitude of data-intensive mobile applications. This increase in demand is anticipated to push systems to their limits **(Fakhri et al., 2019)**. To meet this escalating need, millimeter Wave (mmWave) technology offers a solution for addressing capacity constraints **(Akdeniz et al., 2014; Wang et al., 2019)**. A key advantage of mmWave is its bandwidth compared to sub-6 GHz frequencies, which can greatly enhance network capacity. Operating within the 30 to 300 GHz range mmWave is positioned to play a role as a technology of choice. However, these frequencies have a limited range **(Dehos et al., 2014)**. May experience performance issues due to obstacles and significant signal losses **(Fang et al., 2021; Banar et al., 2022).** In this context, cloud radio access network (C-RAN) **(Luo et al., 2020; Kai et al., 2021)** appears as a favorable new infrastructure that objectives to enhance the use of mmWave spectrums and improve performance in 5G networks and future wireless systems **(Pompili et al., 2015; Hajisami and Pompili, 2018)**. BBU and RRH are the two main components that make up a CRAN. BBUs are placed in the cloud as clusters in the BBU Pool, which has all information about the network, whereas all RRHs are distributed in the network over multiple sites, which are connected to the BBUs through wireless links or fiber optic cables based on the network requirements **(Kolawole et al., 2018; Obi et al., 2023)**. Periodically, based on reports received from users through associated RRHs network information is updated to the controller in the BBU pool, including location coordinates and coverage areas of all known RRHs to the controller, who then runs algorithms for handover and engagement decisions, which are then transmitted to the RRHs. As a result, C-RAN is considered a cost-effective solution for network densification, reducing resource consumption, and managing future communication network interruptions **(Taleb et al., 2018).** In the initial deployment of mmWave cellular communications, especially in dense urban environments, Heterogeneous Cloud Radio Access Networks (HC-RANs) prove highly effective in enhancing network performance. This is achieved through the deployment of ultra-dense mmWave small base stations (SBSs) coexisting with conventional macro base stations (MBSs) within a multi-band heterogeneous network architecture **(Fakhri et al., 2019)**. Despite these advantages, HC-RN switching is expensive and presents serious challenges. These include the integration of technology models and the gradual implementation of heterogeneous network architecture. Furthermore, the high frequency and the unique propagation characteristics of mmWave signals result in unprecedentedly large intercellular interference **(Noor and Omran, 2018)**, especially at the cell edges. Therefore, developing effective interference management strategies is crucial and remains a hot research topic **(Trabelsi et al., 2024)**. The rapid development of technology in recent years has been accompanied by a rapid expansion of machine learning (ML) applications in numerous studies in all fields **(Al-Araji and Al-Zangana, 2019; Mohammed and Hussein, 2022; Abdulrezzak and Sabir, 2023)** especially in wireless networks. This growth has been mainly driven by ML **(Haidine et al., 2021)**. Machine learning has become an integral part of 5G networks and is expected to be a key driver of future mobile and 6G technologies **(Nguyen et al., 2021).**

The contributions of this paper are outlined as follows:

- Representation and Evaluation: present, verify, and evaluate a two-tier HC-RAN system based on various performance criteria, considering actual network load and deployment

scenarios. By using different frequency ranges for each tier, aiming to mitigate interference and improve rate and coverage, not only at the cell edges but throughout the entire cell area.
- Interference Mitigation: address inter-RRHs interference for the association between User and RRH. Specifically, by employing an online Multi-Agent-Q-Learning (MAQL) algorithm to improve network throughput, thereby improving the Quality of Service (QoS) for end users and boosting overall network performance.

In communication networks, researchers have explored interference mitigation strategies and the application of machine learning techniques, some of which are highlighted. In **(Wang et al., 2019)**, the authors studied coverage in multi-tier downlink mmWave HC-RAN with user-centric smallcell deployments, in order to enhance user connectivity and its performance by focusing on techniques of interference mitigation, as well as taking into consideration user and base station location associations, and mmWave communication characteristics. Their results refer that when set the transmitted power of macro base stations (MBSs) whereas the transmitted power of small cell base stations increases, improving coverage probability. To improve data rates in large cell areas leverage mmWave spectrum the authors **(Fakhri et al., 2019)** proposed approach based on soft frequency reuse (SFR) for the interference mitigation between MBSs, the cellular service region is divided into two sub-regions, each of tier is operated by distinct frequency range in order to prevent cross-tier interference. The center region is served by conventional MBSs which operate in the sub-6 GHz frequency band, while the edge area is served by Remote Radio Heads (RRH), which operate in the millimeter-wave frequency band. Thus, this model targets the entire cell area. Using stochastic geometry techniques in 5G, the authors **(Fang et al., 2021)** assessed the performance of two-tier heterogeneous networks by taking into account various biases, which can help in improving load distribution across tiers; they get a formula for cell association probabilities. In addition to mitigating interference and forming an association with users, they proposed a method based on the least path loss as criteria. Based on machine learning, the authors **(Elsayed et al., 2020),** mitigate interference in mmWave 5G networks. The aim of their approach is optimizing resource allocation and user-cell association to enhance the network's overall sum rate by implementing an algorithm designed to manage power distribution between packets and user-cell associations by generating a priority list of 5G-NodeBs, often referred to as gNBs in 5G networks, are the next generation of base stations in the 5G architecture, organized according to average SINR.

In **(Cheng et al., 2021)** they propose a learning-based interference management mechanism for smallcells, combining hybrid affinity propagation clustering and reinforcement learning in power control. by identifying and deactivating the most interfering aerial small cells, simplifying the interference structure and accelerating the learning process. A proposal for a mmWave C-RAN for 5G was introduced by **(Banar et al., 2022),** the study evaluated the performance of mmWave by comparing RRH association methods for half-duplex and full-duplex configurations, with a focus on the interference. The evaluation took into consideration factors such as path loss, obstructions, directivity of fronthaul and access links, and the characteristics of the mmWave channel. Within the framework of interference mitigation between dense small cells and to minimize call blocking and solve load balancing issues, optimizing performance for each user, the authors **(Suresh et al., 2022)** suggested a cat swarm optimization algorithm to find the optimal RRH configuration across the network. A novel strategy called Multi-Agent Context Learning addressed by the authors

**(Kose et al., 2024)** to manage interference and allocate mmWave beams, maintain low interference levels even during heavy traffic by utilizing Contextual Bandit techniques, the agent of machine learning could identify and avoid interference with other transmissions based on understanding the status of neighboring beams as criteria. For the purpose of interference mitigation in this paper, we adopted a strategy that improves user-RRH association to maximize network throughput for mmWave RRH by applying an online (MAQL) algorithm to form associations with users in mmWave communications in 5G networks.

## 2. SYSTEM MODEL

### 2.1 Network Deployment

The proposed model is a two-tier HC-RAN deployed in ultra-dense networks. The first tier consists of high-power macrocells arranged in a hexagonal grid and served by MBS, which provide good coverage and support for high mobility and a responsible for ensuring essential connectivity over a wide area as well as serving users at greater distances, which are positioned at higher altitudes and supplied with greater transmission power. The second tier is comprised of low-power small cells served by mmWave RRHs to enhance capacity and coverage in smaller, densely populated regions, enhancing network performance in hotspots with high user density. Typically, RRHs are deployed at lower altitudes, such as rooftops or street elements, and have lower transmission capacities compared to MBSs, RRHs are organized into clusters, where each cluster consists of several geographically adjacent RRHs. Typically, RRHs are distributed within macrocells to cover the whole cell region **(Fakhri et al., 2019).** To avoid the frequent handovers and mmWave channel blockages in C-RAN, the BBUs are separated from the RRHs, which are consolidated into a centralized BBU pool controller. The management and coordination are designed between tiers to efficiently spread network traffic between MBSs and RRHs to prevent congestion and optimize resource utilization. This involves the challenge of choosing which users should be served by MBSs or RRHs depending on factors such as capacity, user demand, and signal quality. These procedures are handled within the BBU pool, where smallcells (RRHs) of mmWave HC-RANs are accessed via fronthaul links. In addition, by using backhaul links and control interfaces, MBSs associated with BBU pool, according to 3GPP specifications **(Khan et al., 2018; Rodoshi et al., 2020).** The complication of the proposed model produces several types of interference, including interference between MBSs, interference between MBSs and smallcell RRHs, and interference among the smallcell RRHs themselves. The suggested paradigm uses the SFR method **(Fakhri et al., 2019; yağcıoğlu, 2022)** to mitigate interference between MBSs. The cellular serving area is divided into two regions, each operating on a distinct frequency spectrum to avoid cross-tier interference. The center region is served by MBSs operating in the sub-6 GHz frequency spectrum, while the edge area is served by RRHs operating in the mmWave frequency spectrum **(Fang et al., 2021).** This method improves overall cell coverage, interference mitigation, and user throughput, the suggested network architecture illustrated in **Fig. 1.** On the other hand, the Inter-RRH interference among mmWave smallcells will be addressed in the proposed algorithm.

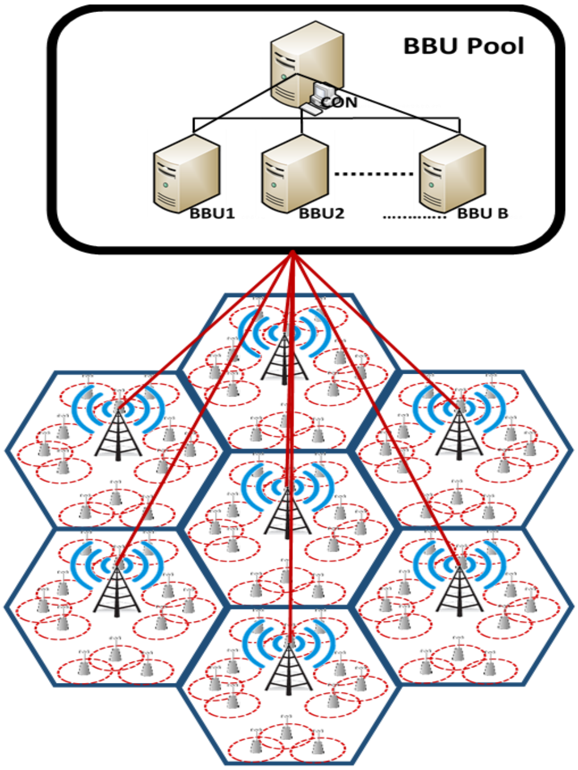



**Figure 1.** The proposed HC-RAN Network.

## 2.2 Channel and Path Loss Model

This paper takes into consideration a channel model appropriate for a two-tier downlink heterogeneous wireless network. This model considers the characteristics of mmWave frequencies, making it multilateral for use in various 5G network scenarios, which is essential for enhancing the capacity and coverage of mmWave systems. It includes two sub-models **(TSGR, 2022)**: an Urban Macro (UMa) channel model for an MBS hexagonal grid with an antenna in the center of each MBS that operates in sub-6 GHz, which represents the first tier of the network. The second type of channel is an Urban Micro Street Canyon (UMi) for mmWave RRHs, which represents the second tier of network that overlaid each MBS to cover the cellular edge area. While users are distributed using uniform random distribution across the network. Users close to cell boundaries experience boundary effects, represented by interference between mmWave smallcells **(Mohammed and Almamori, 2024).** In the first tier of the network, which is represented by macrocells, there is interference power received by the user k from all other macrocells, except the macrocells that served the same user k, and the equation of signal-to-interference plus noise ratio (SINR) is formulated as follows **(Fakhri et al., 2019; Fang et al., 2021):**

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

Where pointing out the usage of "i" indicates the serving MBS for user k, while "j" indicates to other MBSs, $\sigma_m^2$ is the noise power, $P_{m_i}$ is the downlink transmited powers of MBS, and $G_{k_{m_j}}$ is a combination channel gain, which composed of channel fading and path loss, which is given as follows:

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

Where $g_{m_i}$ is the antenna gain of MBS, $s_{m_i}$ represents small scale fading channel, which is supposed as Rayleigh random variable, $l_{m_i}$ the large scale channel fading, which is supposed as lognormal shadowing **(Andrews et al., 2016)**, and $PL_m\,(d_m)$ denote the UMa path loss for k user linking to a MBS from 3GPP TR 38.901**(Zhu et al., 2021; TSGR, 2022),** given for LOS and NLOS cases as follow:

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

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

Where:

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

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

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

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

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

$$d_{BPm} = \frac{4\grave{h}_{MBS}\,\grave{h}_k\, f_{cm}}{c} \quad (9)$$

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

$\sum_{j \in M, j \ne i} P_{m_i} . G_{k_{m_j}}$ indicates the interference power received from other MBSs.

In the second tier of network which is represented by RRHs. The dense deployment of RRHs may result in an inter-RRH interference power received by the user k from all other RRHs, with the exception of the RRH that served the user k, therefore SINR formulates as follows **(Fakhri et al., 2019; Fang et al., 2021)**:

$$SINR_{k_r} = \frac{P_{r_i} . G_{k_{r_i}}}{\sum_{j \in R, j \ne i} P_{r_j} . G_{k_{r_j}} + \sigma_r^2} \quad (10)$$

where pointing out the usage of "i" indicates the serving RRH for user k, while "j" indicates other RRHs, $\sigma_r^2$ is the noise power, $P_r$ is the downlink transmit powers of RRHs and $G_{k_{r_i}}$ is a combination channel gain, which is composed of channel fading and path loss, which is given as follows:

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

where $g_{r_i}$ is the antenna gain of RRH, $s_{r_i}$represents small scale fading channel, which is supposed as a Nakagami with normalized gamma distribution **(Simon and Alouini, 2005)**, $l_{r_i}$ is large-scale fading channel, which is supposed to lognormal shadowing **(Andrews et al., 2016),** and$PL_r(d_r)$ denote the UMi path loss for user k linking to an RRH from 3GPP TR 38.901 **(TSGR, 2022)**, given for LOS and NLOS cases as follows:

$$PL_{rLOS}(d_r) = \begin{cases} PL_{r1}, for\ 10m \le d_{er} \le d_{BPm} \\ PL_{r2}\ , for\ \ d_{BPm} \le d_{er} \le 5km \end{cases} \tag{12}$$

$$PL_{rNLOS}(d_r) = max\left(PL_{rLOS}(d_r), P\grave{L}_r(d_r)\right), for 10m \le d_{er} \le 5km \tag{13}$$

where:

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

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

$$P\grave{L}_r(d_r) = 22.4 + 21.3\ log_{10}(f_{cr}) + 35.3\ log_{10}(d_r) - 0.3\ log_{10}(h_k - 1.5) \tag{16}$$

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

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

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

where$f_{cr}$ is the carrier frequency of RRHs and c is the speed of light, $\grave{h}_{RRH} = h_{RRH} - h_E$, and $\grave{h}_k = h_U - h_E$, represent effective heights of antenna at RRH and user, respectively, $h_{RRH}$ represents the actual heights of antenna. $\sum_{j\in R, j\neq i} P_{r_j} \cdot G_{k_{r_j}}$ indicates the interference power received from all other RRHs.

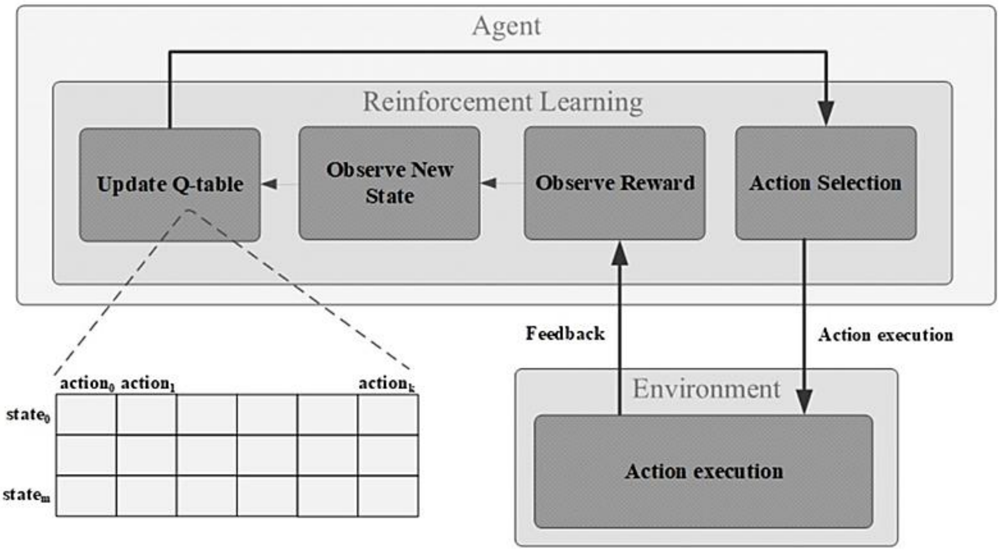
## 3. FORMULATION THE PROPOSED MACHINE LEARNING

### 3.1 Overview on Q-learning

Q-learning is a form of reinforcement learning where an agent interacts with an environment in order to achieve a specific objective. The agent learns about the environment's dynamics through trial and error. It receives feedback in the form of rewards or penalties as it acts, which also results in changes to the environment's state, as shown in **Fig. 2.** This interaction may be formalized like the Markov Decision Process (MDP) **(Watkins and Dayan, 1992; Elsayed et al., 2020)**, characterized by a group consisting of reward function, actions, states, and agents. The main goal of the agent is to optimize the overall projected rewards over time, adjusted for future discounting.
To accomplish this, the agent discovers an optimal policy that dictates the best action to take in each state, which is achieved through an action-value function that assesses the

potential value of different actions **(Jang et al., 2019)**. This is achieved through the application function of action-value, which is expressed as:

$$Q(s,a) = \mathbb{E}[R + \gamma \, max_{a'} Q(s',a')|s,a] \tag{19}$$




The function $Q(s,a)$ is the action-value function, i.e. Q-value, representing the expected return or utility of taking action in state s and adopting the optimal policy afterwards, R denotes to reward value obtained after taking action an in-state $s$, while γ represents the factor of discount, which influences the significance of future rewards (0 ≤ γ ≤ 1), whereas $max_{a'} Q(s',a')$ represents the highest expected future reward for the next state $s'$ across all feasible actions a′. In practice, the Q-learning algorithm updates the Q-values using the following update rule:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \, [R + \gamma \, max_{a'} Q(s',a') - Q(s,a)] \tag{20}$$

where α is the learning rate (0 < α ≤ 1), controlling how much new information overrides the old value. In this work we introduced the proposed Q-learning algorithm designed to optimize user-RRH association in order to maximize the network's throughput.

### 3.2 Optimization Problem Formulation

Since each tier works at a distinct frequency band, as explained in the above Eq. (1) and Eq. (10), the proposed network does not suffer cross-tier interference, and it also does not suffer inter-cell interference between macrocells in the first tier because the use of the SFR method. In this case, the interference is only between the mmWave RRHs. The BBU pool controller maintains network comprehensive information. This information is updated regularly using reports from users across the associated RRHs. The controller has access to the position coordinates and coverage region of all RRHs. It is responsible for implementing the algorithms that manage handover and link decisions, which are subsequently communicated to the RRHs. Assume there are K number of users and $R$ number of RRHs. The average throughput of a user, denoted by $Th_{k,r}$, is dependent 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 with RRH $r$ and allocated to BBU s, is expressed as follows **(Taleb et al., 2020):**

$$Th_{k,r} = \frac{T_{k,r}}{k_r} \tag{21}$$

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

$$T_{k,r} = W_r \ log_2(1 + \ SINR_{k,r}) \tag{22}$$

where $k_r$ indicates the number of users that sharing the RRH r radio resource, as follows:

$$k_r = \sum_{r \in R} X_{k,r} \tag{23}$$

The optimization problem (TH) aims to mitigate interference by finding the user k associated with suitable RRH $r$ to maximize the total user throughput in the network which depends on Eq. (21) and Eq. (22), is expressed as follows:

$$max\ (TH) \ = \sum_{r \in R} \sum_{k \in K} X_{k,r} \ Th_{k,r} \tag{24}$$

where$X_{k,r}$ is the complexity solution matrix to make the decision about which User-RRH association solution is the best, and subject to the following constraints:

$$\sum_{r \in R} X_{k,r} \ \ \leq 1 \ , \forall k \ \in K \tag{25}$$

$$X_{k,r} \ \leq t_r, \forall r \ \in K \times R \tag{26}$$

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

The constraint in Eq. (25) refers that every user k in the network can at most be associated to a single RRH r. The constraint in Eq. (26) illustrates that each RRH $r$ is activated only when it is connected with one user k at least. The constraint in Eq. (27) show that the variables $X_{k,r}, t_r$ are binary decisions. We adopted a User-RRH association strategy suitable for mmWave communications in 5G HC-RAN network to eliminate inter-RRH interference in a way that maximizes the overall throughput of the network achieved by the user. In order to solve the problem, the User-RRH association is solved by using the Proposed Q-learning algorithm.

### 3.3 The Proposed Q-Learning

The proposed online MAQL algorithm for is described as follows:

- **The Agents:** RRHs
- **The Actions:** The actions available to each RRH (agent) are the different users they can choose to associate with. The action vector $ai$ represents the choice of RRH for user $i$.
- **States:** the state for each RRH (agent) is the context or situation in which the RRH is making its decision. In this case, the state for each RRH can be represented by the path loss values to all Users. Specifically, for each RRH$i$, the state is a vector of path losses from that RRH with each user. Therefore, the state vector State$i$ for RRH $i$ is represented by the vector:

$$S_i = [s_1, s_2, s_3, \ldots\ldots\ldots\ldots s_k] \quad (28)$$

This vector directly represents the state of the agent environment and is used to determine the RRH to associate with the user based on the current policy (exploration or exploitation).

- **Reward:** the reward is a measure of how good or bad an action (associating with a particular RRH) is. In this case, the reward is based on the path loss; specifically, the reward is the negative of the path loss to maximize SINR (which corresponds to minimizing path loss). Therefore, the reward function R is formulated based on the least path loss as follows:

$$R_i = -PL(RRH_i) \quad (29)$$

Furthermore, the user-RRH association procedure includes the learning part within RRH's side by generating a list of priority for RRHs ranked according to the least path loss path loss **(Lee et al., 2015; Fang et al., 2021)** to create association with users, then users are associated with the RRH with a preferred value in the list of priorities. To demonstrate the effectiveness of the proposed algorithm, it was compared with another online MAQL algorithm in a previous study **(Elsayed et al., 2020)** that associates a user to the cell by generating a list of priorities for 5G-NodeBs ranked depending on average SINR. Then, users are associated with 5G-NodeBs with preferred value in the list of priorities; this was applied for two types of deployment scenarios for mmWave RRHs in the proposed system under NLOS conditions, for simplicity and understanding, the Q-Learning algorithm steps illustrated in pseudo-code in Algorithm 1.

**Algorithm 1:** MAQL Algorithm For User-RRH Association

**Input:** Q (s, a) = 0, α, γ, ϵ, Users' positions, RRHs' positions, Path loss estimations between users and RRHs
Output: Final user-RRH association decisions

**Begin**
1: Initialize Parameters: $Q(s, a) = 0$, $\alpha, \gamma, \epsilon$, Set positions of users and RRHs, Estimate path loss between users and RRHs
2: **For** scheduling simulation SIM=1 to No. of Simulation **do**
3: Perform MAQL algorithm for User-RRH association for each state s **do**
4: Compute least path loss for each state s
5: Exploration Vs Exploitation Decision If rand ≤ $\epsilon$ then
6: Action: The decision to associate a user with a best RRH based on exploration or exploitation.
7: else
8: Exploitation - Choose the action with the highest Q-value (Next action: $max_{a'} Q(s', a')$)
9: End if
10: Calculate reward R as negative path loss for the chosen RRH as in Eq. (29).
11: Update Q-value for the best User-RRH using Q-learning update rule as in Eq. (20).
12: Transition to the next state $s'$
13: Transmit User-RRH association decisions to each user.
14: The user performs the final User-RRH association decisions
15: End for
16: End for
**End**

## 4. PERFORMANCE METRICS

### 4.1 The Coverage Probability

This network assumed open access, which is unconstrained, meaning that user can associate with any tier of MBS or RRH without any constraints **(Hassan and Fernando, 2020).** Hence, Positive power biasing and least path loss are used to switch more edge users from the MBS tier to the RRH since MBS transmit at a higher power than RRHs. For example, a user would associate with a RRH if:

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

Moreover, if not, a user would associate to an MBS, where $PL^{-1}_{min,m}(d), PL^{-1}_{min,r}(d)$ refer to the minimum path loss of user connecting to the MBS, and RRH respectively, and $B_m$, $B_r$ work as a user association biasing factor with MBS, and RRH respectively. Depend on maximum received biased power, user linked to the MBS in the center area have $B_m$ =0dB, while $B_r$ >0 is for user linked to a RRH and situated in the cellular edge area. The coverage probability is introduced in a scenario where users are located in network coverage, where each user associates to a defined cell, if their SINR is above a predefined threshold SINR ($\mathcal{T}_c$).

$$P_{SINR}(\mathcal{T}_c) = P(SINR > \mathcal{T}_c) \tag{30}$$

The coverage probability ($P_{SINR_k}$) of the suggested network can be introduced by the following **(Fakhri et al., 2019; Hassan and Fernando, 2020):**

$$P_{SINR_k}(\mathcal{T}_c) = \mathcal{A}_m P_{SINR_{km}}(\mathcal{T}_c) + \mathcal{A}_r P_{SINR_{kr}}(\mathcal{T}_c) = \left(\cup_{j\in\{m,r\}} \mathcal{A}_j\, P(SINR_{kj} > \mathcal{T}_c)\right) \tag{31}$$

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

### 4.2 Rate Coverage Probability

The rate achieved for the user can be given as follows:

$$\mathcal{R}(K_j) = log_2\left(1 + SINR_{k_j}\right), j \in \{m, r\} \tag{32}$$

The rate coverage probability in an open access network is introduced when users are considered to be within rate coverage in the network, if their downlink rate is above a predefined threshold rate ($\rho_r$). Therefore, Rate Coverage Probability:

$$\mathcal{R}(\rho_r) = P(\mathcal{R} > \rho_r) \tag{33}$$

Thus, the rate coverage probability $\mathcal{R}(\rho_r)$ of the suggested network is presented by the following expression **(Fakhri et al., 2019)** as follows:

$$\mathcal{R}(\rho_r) = \cup_{j\in\{m,r\}} \mathcal{A}_j \ P\left( log_2 \left(1 + SINR_{k_j}\right) > \rho_r\right) = \cup_{j\in\{m,r\}} \mathcal{A}_j \ P\left(SINR_{k_j} > (2^{\rho_r} - 1)\right) \quad (34)$$

## 5. SIMULATION IMPLEMENTATION SCENARIO

Simulation results for the proposed system's architecture are obtained using MATLAB, while the analysis with 100 iterations is conducted to evaluate the proposed system performance based on the general simulation parameters outlined in **Table 1**. The proposed online MAQL algorithm associates the user with RRH by generating a priority list of RRHs ranked according to the least path loss. Then, users are associated with the RRH with a preferred value in the list of priorities. To demonstrate the effectiveness of the proposed algorithm during simulation, it was compared with another online MAQL algorithm that associates a user to the cell by generating a list of priorities for 5G-NodeBs ranked depending on average SINR. Then, users are associated with 5G-NodeBs with preferred values in the list of priorities; this was applied for two types of deployment scenarios for mmWave RRHs in the proposed system under NLOS conditions.

**Table 1**. Simulation Parameters

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| No. of Users | 70 - 1000 | Sub-6 GHz noise power ($\sigma_m^2$) | -174dBm/Hz |
| No. of macrocells (MBSs) | 7 | mmWave noise power ($\sigma_r^2$) | -174dBm/Hz |
| No. of smallcells (RRHs) | 84 | Uma Shadow fading for NLOS | 6dB |
| Radius of macrocells | 500m | UMi Shadow fading for NLOS | 7.82dB |
| Radius of smallcells | 100m | Transmit powers of RRH ($P_r$) | 30 dBm |
| Sub-6 GHz carrier frequency | 2GHz | Transmit powers of MBS ($P_m$) | 44 dBm |
| mmWave carrier frequency | 28GHz | Learning rate (α) | 0.1 |
| Sub-6 GHz bandwidth ($W_m$) | 20MHz | Discount factor (γ) | 0.9 |
| mmWave bandwidth ($W_r$) | 1GHz | Exploration probability ($\epsilon$) | 0.1 |

## 6. RESULTS AND DISCUSSION

**Fig. 2** shows the simulation result of a two-tier HC-RAN network deployment model proposed, **Fig. 2(a)** represents the simulation result of the network deployment model for mmWave smallcells, using uniform random distribution within the macrocells, while **Fig. 2(b)** represents the simulation result of arranging mmWave smallcells on the edges. The reason for this comes against the backdrop of obtaining different results proving the effectiveness and performance of the proposed system.
**Fig. 3** shows the effectiveness of user-RRH association solution in inter-RRH interference mitigation for both deployment scenarios, as each user is associated with at most one RRH according to the first constraint in Eq. (25) which states “that every user k can at most be associated to a single RRH r". Any RRH that is associated with at least one user is activated and appears in red, while an inactive RRH appears in green indicating that it is inactive and in sleep mode because it is not associated with any user. **Fig. 4** displays the average network throughput versus the number of iterations under the same network conditions and with the same number of RRHs while serving 500 users for both random and on-edge deployment. It was observed from the general trends that the proposed online MAQL (UA EQ) solution outperforms the other online MAQL (UA Q) solution when applied to both deployment strategies by 13.9% and 9.57%, respectively.

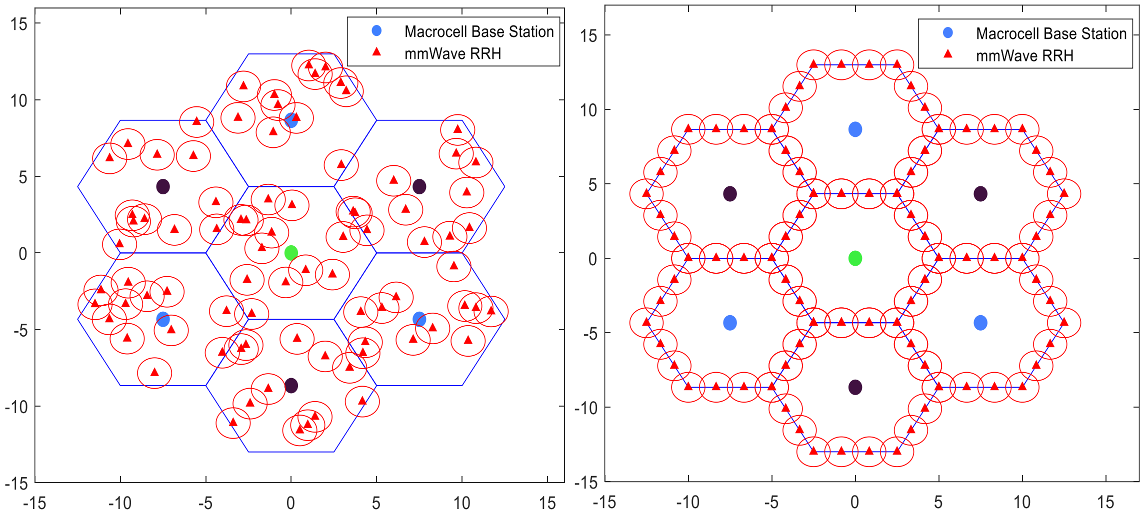



**Figure 2.** Comparison scenarios of network (a) Random RRHs (b) On edges RRHs.

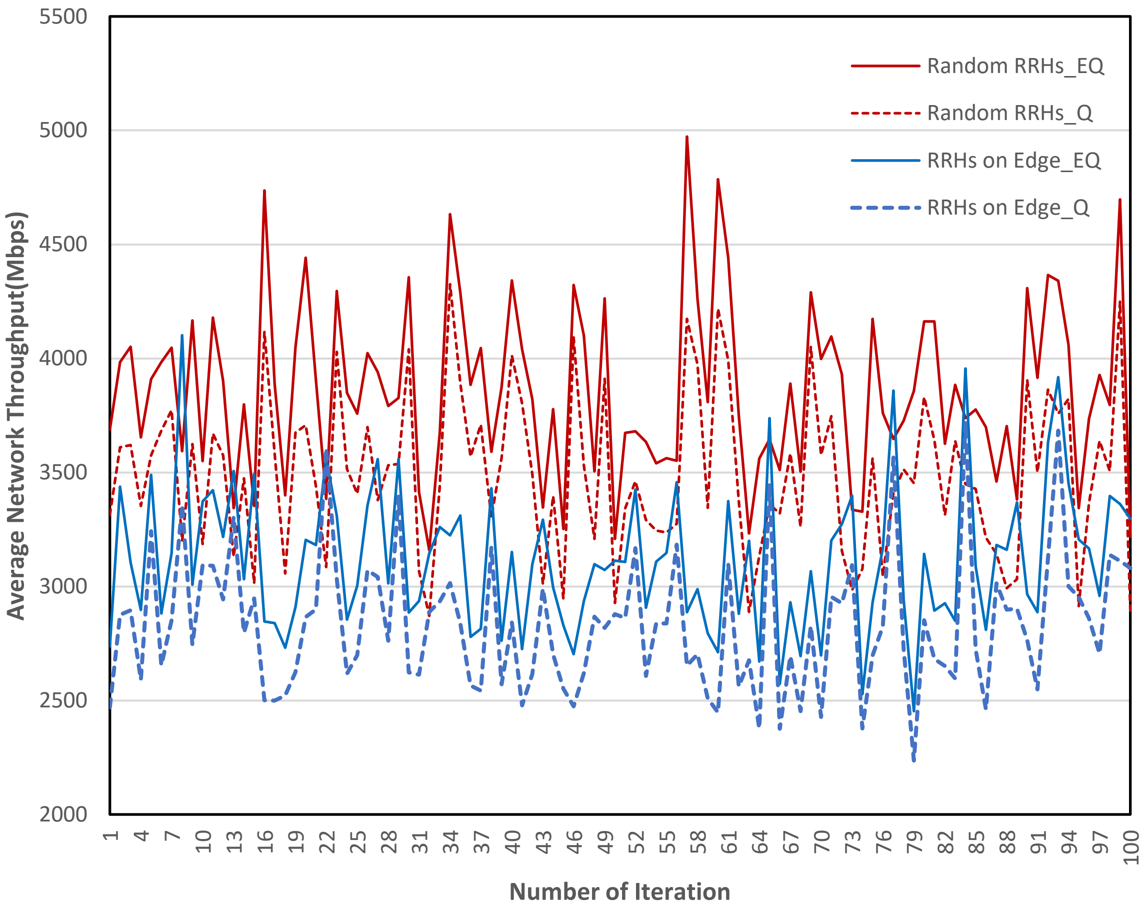



**Figure 3.** User Association with Active RRHs (a) Random RRHs (b) On edges RRHs.

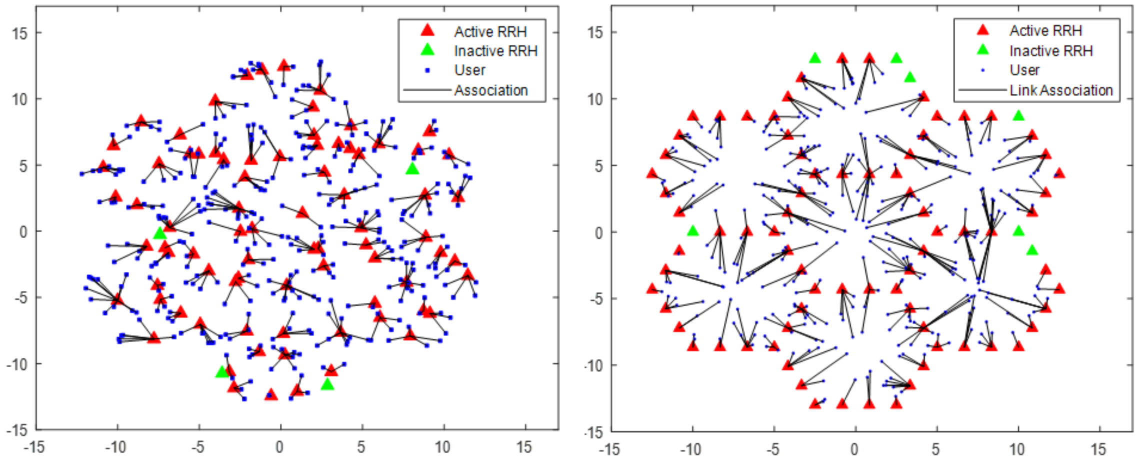



**Figure 4.** Average Network for User-RRH association.

This is due to following the optimal resource utilization policy. Using the best selection policy during exploration leads to more efficient signal routing and reduced signal loss. In addition to effective load distribution of users across RRHs with the best signal strength despite obstacles, which reduces congestion on specific units and leads to improved overall performance, reducing interference between different users contributes to increasing the maximum productivity that can be achieved. These findings confirm the effects of the suggested UA EQ algorithm in enhancing wireless communication systems, contributing to improved quality of service and reduced interference in both random and edge network deployments in the proposed system.

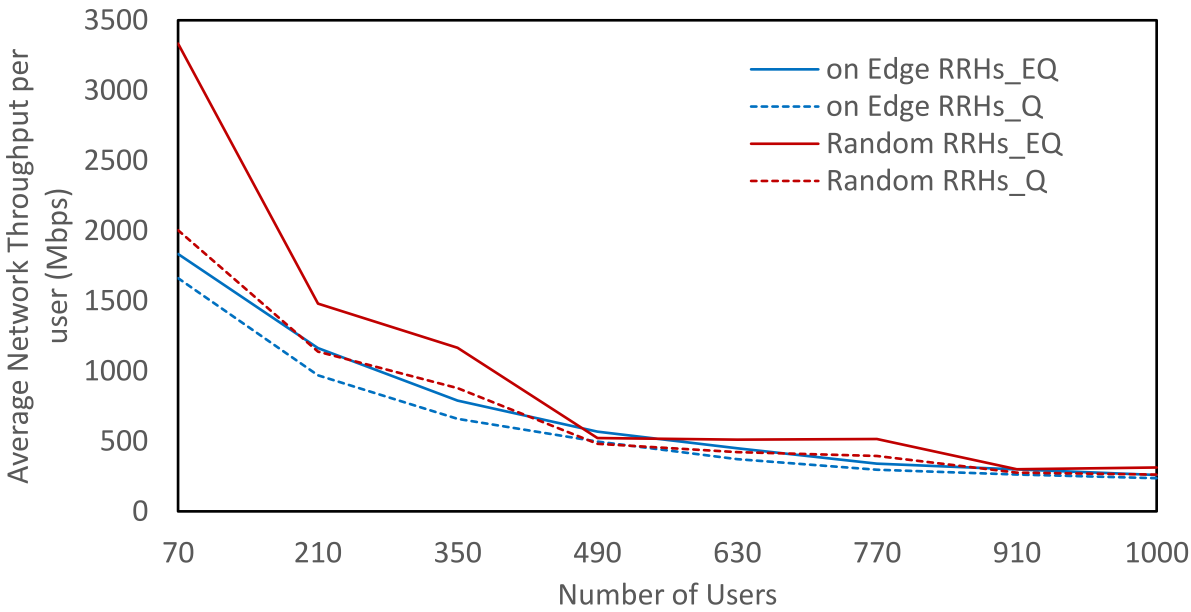



**Figure 5.** Average Network Throughput per user for User-RRH association.

**Fig. 5** shows the average network throughput as a function of the number of users under the same network conditions and with the same number of RRHs for both random and on edge deployment, given as the total throughput achieved within the network over total users

connected to the network. which offers a user-centric perspective, reflecting the experience of individual users within the system. The general trend in both scenarios of deployment is that average throughput decreases as the number of users increases. The reasons for this fact are: resource allocation: when there are fewer users, each user can have more of the network's resources allocated to them, such as bandwidth and processing power.
Reduced Congestion: With fewer users, there's less competition for network resources, leading to reduced congestion and faster data transmission.
Improved Efficiency: When network resources are not heavily utilized, they can be used more efficiently, resulting in higher throughput.
However, it's important to note that this relationship is not always linear. As the number of users increases, the network may be able to utilize its resources more efficiently through techniques like load balancing and resource allocation optimization. Beyond a certain point, though, increasing the number of users can lead to diminishing returns and even decreased throughput this behavior is consistent with the principles of network congestion and interference, where more users share the available bandwidth, reducing individual throughput.
The highest user throughput was obtained with the proposed problem online MAQL (UA EQ) solution compared to the other online MAQL (UA Q) solution when applied to both random and on-edge deployment strategies by 66.4% and 21%, respectively, at the lowest number of users. The difference gradually decreases with increasing user numbers until it reaches 8.7% and 9.8%, respectively, but the difference remains noticeable even with increasing user numbers. In random deployment of RRHs, it generally achieves the highest throughput for each user, indicating that specific UA EQ might be more effective than applied on edge deployments. This might be due to better management of the higher user density and specific geographical challenges over the whole cell area. The proposed problem online MAQL (UA EQ) solution distributes the load more effectively, leading to higher overall throughput per user. This indicates better utilization of available resources and more efficient interference reduction. Provides a more consistent and higher quality of service for individual users due to better load distribution and interference management. Users experience higher throughput, leading to better overall performance and user satisfaction. Even though the gap between throughput performance narrows as user density increases, the proposed method consistently outperforms the alternative strategy, indicating its ability to adapt and manage network resources more effectively even under higher traffic loads.
**Fig. 6** shows the numerical simulation results of SINR coverage probability performance for various scenarios with the same number of mmWave RRHs and users under the same network conditions where mmWave RRHs are either randomly deployed or placed at the edges of the macrocells. The general trends in each deployment scenario indicate that the probabilities of coverage are high and convergent at the lowest SINR threshold values (from -10 to 0) for all scenarios. As the SINR threshold increases from 0dB to 30dB, there is a steeper decline in coverage probability, this gradual decline is attributed to obstacles and multipath fading in environments. At higher SINR thresholds, notable differences emerge between scenarios. Specifically, random deployments tend to outperform edge deployments at higher SINR thresholds by approximately 26.7% and 27.81%, respectively. The results emphasize the significance of strategic deployment of cell sites (RRHs) deployment, whether at the edge or randomly distributed in network design. This is vital for network planning to improve SINR coverage probabilities, especially when aiming to meet high quality of service standards. Also, the proposed online MAQL (UA EQ) solution tends to outperform the other

online MAQL (UA Q) solution when applied to both deployment strategies at higher SINR thresholds by approximately 8.8% and 9.9%, respectively. Generally, random RRHs deployments provide better coverage probability across all SINR thresholds compared to RRHs on Edge. The proposed online MAQL (UA EQ) shows an overall improvement in coverage probability over the other online MAQL (UA Q), regardless of the RRHs deployment type.

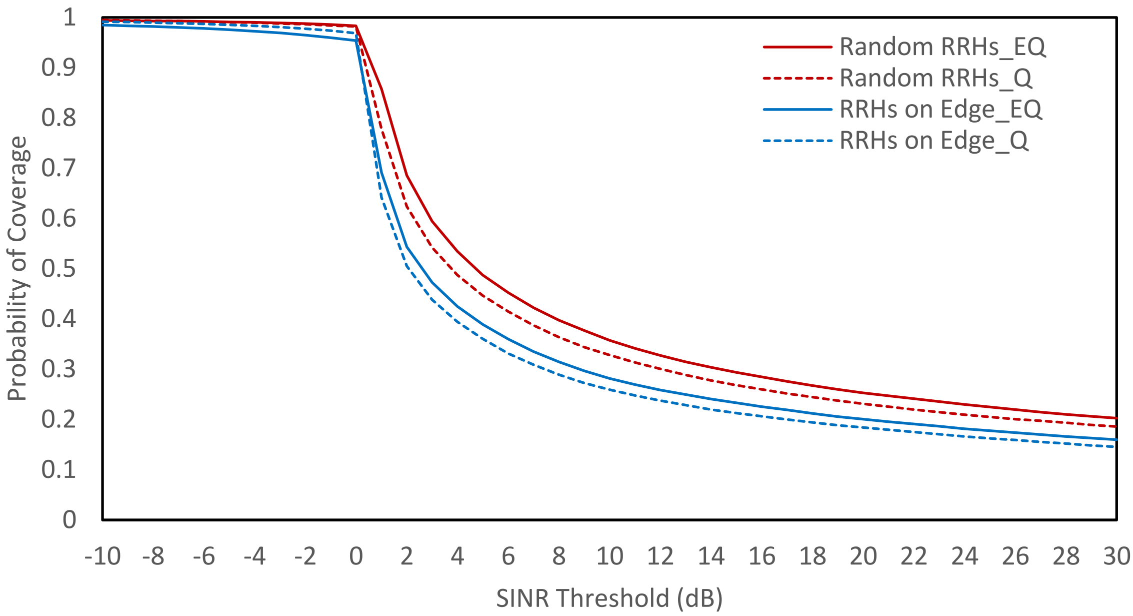



**Figure 6**. Coverage Probability Performance.

**Fig. 7** shows a rate coverage probability comparison for HC-RAN across different deployment scenarios, random and on edge deployment, which was also conducted under the same network conditions and with the same number of RRHs and users. At the outset, scenarios exhibit high coverage probabilities near or at 1 when the rate threshold is zero, indicating that nearly all cells can provide minimal rates. However, as the rate threshold increases, the probability that a cell can meet this rate declines. This is expected since sustaining higher data rates is more challenging across various locations and conditions within the network. Random RRH deployments are more effective at meeting higher rate demands, with average gains of 28.52% and 26% in rate coverage probability compared to on-edge RRH deployments. This suggests that on-edge RRHs deployment generally provides the lowest coverage across various rate thresholds. The proposed online MAQL (UA EQ) solution is more effective at meeting higher rate demands, with average gains of 9.3% and 7.1% in rate coverage probability compared to the other online MAQL (UA Q) solution, regardless of the RRHs deployment type. The observations underscore that using the proposed online MAQL (UA EQ) approach with different cell deployment strategies significantly influences network performance. Random RRH deployments prove more effective than edge deployments, offering better rate coverage probability and adapting more adeptly to real-world challenges such as obstacles, user distribution, and interference.

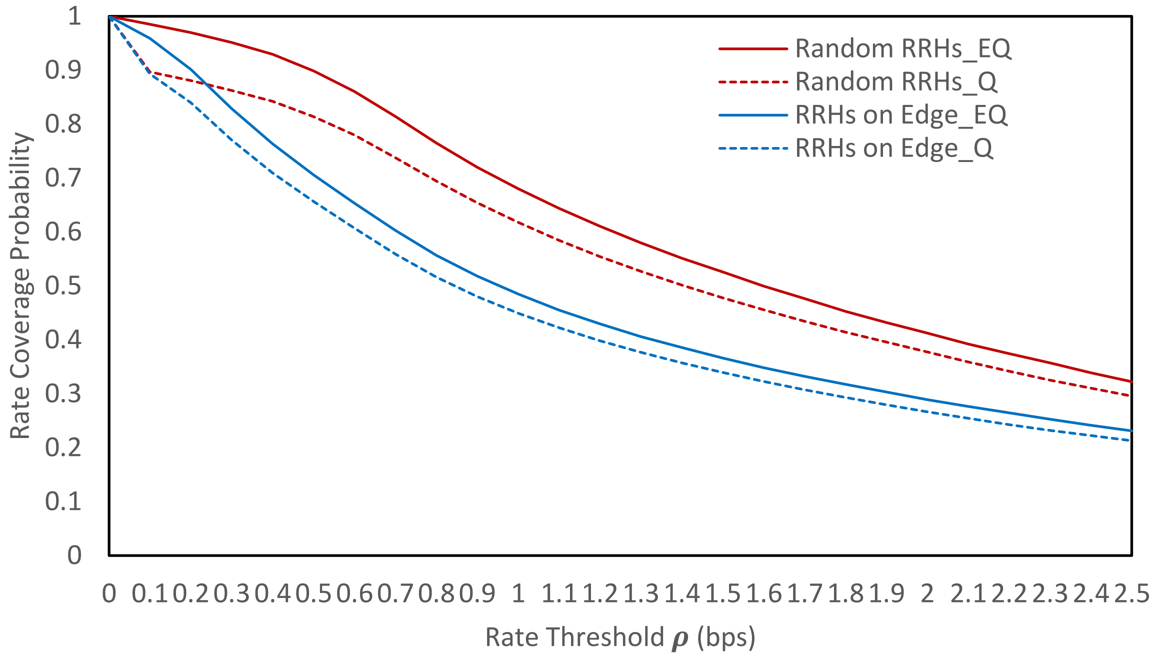



**Figure 7.** Rate Coverage Probability.

## 7. CONCLUSIONS

This paper presents an online MAQL algorithm to handle User-RRH association problem for mmWave HC-RAN in 5G systems for interference mitigation and to maximize total throughput in the network. The suggested algorithm associates the user with the RRH having each agent generate a priority list of RRHs ranked according to the least path loss between it and all users in its environment for two types of deployment scenarios and compared with another online MAQL algorithm in a previous study that associates the user with the cell by having each agent associate the user with the cell by generating a priority list of 5G-NodeBs ranked according to the average SINR between it and all users in its environment.
Additionally, the strategic deployment of mmWave cell sites within the coverage area of the MBS cells plays a crucial role in enhancing network coverage, rate, and throughput, as well as mitigating interference based on User-RRH association and the prudent use of machine learning techniques, where the simulation results of Q-learning strategies of implementation User-RRH association strategies have proven effective in enhancing network performance and quickly adapting to varying traffic loads.

## NOMENCLATURE

| Symbol | Description | Symbol | Description |
|---|---|---|---|
| $d_m$ | 3D distance between serving MBS and user | $\grave{h}_k$ | Effective antenna height for user |
| $d_r$ | 3D distance between serving RRH and user | $\grave{h}_{RRH}$ | Effective antenna heights for RRH |
| $Q(s,a)$ | action-value | $h_E$ | Effective environment height |
| $h_{MBS}$ | Actual antenna height for MBS | $d_{em}$ | Euclidian distance between serving MBS and user |

| | | | |
|---|---|---|---|
| $h_k$ | Actual antenna height for user | $d_{er}$ | Euclidian distance between serving RRH and user |
| $h_{RRH}$ | Actual antenna heights of RRH | $l_{m_i}$ | Large scale channel fading for MBS |
| $\eta(t)$ | Actual load in the system | $l_{r_i}$ | Large scale channel fading for RRH |
| $g_{m_i}$ | Antenna gain for MBS | α | Learning rate |
| $g_{r_i}$ | Antenna gain for RRH | $\sigma_m^2$ | Noise power for MBS |
| $\mathcal{A}_m$ | Association probabilities for MBS work in sub-6Ghz | $\sigma_r^2$ | Noise power for RRH |
| $\mathcal{A}_r$ | Association probabilities for RRH work in mmWave | $T_{k,r,s}$ | Peak user throughput |
| $d_{BPm}$ | Breakpoint distance for MBS | $\mathcal{R}(\rho_r)$ | Rate coverage probability |
| $d_{BPr}$ | Breakpoint distance for RRH | $\rho_r$ | Rate threshold |
| $f_{cm}$ | Carrier frequency for MBS | $\mathcal{T}_c$ | SINR threshold |
| $f_{cr}$ | Carrier frequency for RRHs | $s_{m_i}$ | Small scale channel fading for MBS |
| $X_{k,r}$ | Complexity for User-RRH association solution | $s_{r_i}$ | Small scale channel fading for RRH |
| $P_{SINR}(\mathcal{T}_c)$ | Coverage probability | $G_{k_{m_j}}$ | Total channel gain for MBS |
| $\gamma$ | Discount factor | $G_{k_{m_j}}$ | Total channel gain for RRH |
| $P_r$ | Down link transmitting powers for RRH | $N_{PRB}^k$ | Total number of Physical Resource Blocks |
| $P_m$ | Downlink transmit powers for MBS | $PL_m$ | UMa path loss for user connecting to MBS |
| $\grave{h}_{MBS}$ | Effective antenna height for MBS | $PL_r$ | UMi path loss for user connecting to RRH |

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## Credit Authorship Contribution Statement

Najwan M. Swadi: writing – review & editing, Writing – original draft, Validation, Software, Methodology. Firas A. Sabir: writing – review & editing, Validation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# التخفيف من التداخل في اتصالات الموجات المليمترية في شبكات الجيل الخامس باستخدام التعلم الآلي المعزز(Q-Learning)

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## الخلاصة

نظرًا لأن تغطية الموجات المليمترية (mmWave) محدودة بسبب فقدان المسار العالي والانسداد، يتم نشرها في خلايا صغيرة. أدى هذا النشر الكثيف لمحطات القاعدة ونقاط الوصول إلى تداخل كبير. لذلك، فإن تخفيف التداخل هو التحدي الرئيسي في تصميم تقنيات اتصالات الموجات المليمترية الجديدة في نظام الجيل الخامس الحالي. في هذه الورقة يتم تقديم نموذج لشبكة وصول راديوي سحابي غير متجانسة (HC-RAN) ذات المستويين، والذي يؤدي تقنية مستوحاة من إعادة استخدام التردد (Soft Frequency Reuse للتخفيف من التداخل. تنقسم منطقة الخدمة الخلوية إلى منطقتين فرعيتين، المنطقة المركزية التي تخدمها محطات القاعدة الكبرى التقليدية، والتي تعمل في نطاق تردد أقل من 6 جيجاهرتز، في حين تخدم المنطقة الحافة رؤوس الراديو البعيدة (RRHs)، والتي تعمل في نطاق تردد الموجات المليمترية لتجنب التداخل بين الطبقات. تم تقديم خوارزمية ارتباطات المستخدمين بوحدات رؤوس الراديو البعيدة للتخفيف من التداخل بين وحدات رؤوس الراديو البعيدة الصغيرة وتعظيم إنتاجية الشبكة باستخدام التعلم الالي متعدد الوكلاء Online Multi-Agent Q-Learning (MAQL). يتفوق حل الخوارزمية MAQL المقترحة ، الذي يعتمد على أقل خسارة في المسار كمعيار أساسي لارتباط المستخدم بوحدات رؤوس الراديو البعيدة، في متوسط إنتاجية الشبكة لكل مستخدم على دراسة سابقة تستند إلى معدل نسبة الإشارة إلى التداخل والضوضاء(SINR average) كمعيار أساسي للارتباط لنوعين من سيناريوهات نشر وحدات رؤوس الراديو البعيدة في الشبكة غير المتجانسة بنحو 66.4٪ و 21٪ على التوالي، عند أقل عدد من المستخدمين. يتناقص الفرق تدريجيًا مع زيادة أعداد المستخدمين حتى يصل إلى 8.7٪ و 9.8٪ على التوالي. على الرغم من أن الفجوة بين أداء الإنتاجية تضيق مع زيادة كثافة المستخدمين، إلا أن الطريقة المقترحة تتفوق باستمرار على الاستراتيجية البديلة، مما يشير إلى قدرتها على التكيف وإدارة موارد الشبكة بشكل أكثر فعالية حتى في ظل أحمال مرورية أعلى.

**الكلمات المفتاحية:** الموجات المليمترية، شبكة الوصول الراديوي السحابية غير المتجانسة ، ارتباطات المستخدمين بوحدات رؤوس الراديو البعيدة.