Learning-based Handover in Mobile Millimeter-wave Networks

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Abstract—Millimeter-wave (mmWave) communication is considered as a key enabler of ultra-high data rates in the future cellular and wireless networks. The need for directional communication between base stations (BSs) and users in mmWave systems, that is achieved through beamforming, increases the complexity of the channel estimation. Moreover, in order to provide better coverage, dense deployment of BSs is required which causes frequent handovers and increased association overhead. In this paper, we present an approach that jointly addresses the beamforming and handover problems. Our solution entails an efficient beamforming method with a minimum number of pilots and a learning-based handover method supporting mobile scenarios. We use reinforcement learning algorithm to learn the optimal choices of the backup BSs in different locations of a mobile user. We show that our method provides high rate and reliability in all locations of the user’s trajectory with a minimal number of handovers. Simulation results in an outdoor real building map data show the superior performance of our proposed solution in achievable instantaneous rate and trajectory rate.

Index Terms—Wireless communications, millimeter-wave networks, handover, reinforcement learning.

I. INTRODUCTION

Due to the high data rate demands in mobile networks, a new era of wireless communication has been started by introducing systems that operate in millimeter-wave (mmWave) bands [1]. The main advantage of moving to the mmWave spectrum is the availability of huge bandwidth in comparison to the conventional sub-6 GHz spectrum. However, mmWave bands are severely affected by obstacles unlike the sub-6 GHz bands for two main reasons. First, due to an order of magnitude smaller wavelength, the signals cannot diffract well against most common materials in urban environments, leading to severe penetration loss and blockage [1]. Second, the need for using directional communication to compensate for the high propagation loss, increases the beam misalignment chance, especially in the presence of many obstacles when there is a need to frequently update the beamforming vectors [2]–[4]. Establishing and maintaining mmWave links are even more challenging in mobile environments where both the users and obstacles are moving. In order to provide good coverage and improve the capacity, base station (BS) densities need to be significantly higher in mmWave network [5], [6]. These bring new challenges when compared to the sub-6 GHz networks [7]. For example, providing a reliable connection through UE’s trajectory while balancing the number of handovers is a key design challenge to be solved if the mmWave networks are to support Gbps data rate for mobile users. In order to address this challenge, an efficient beamforming method is required to enable minimum latency and signaling overhead. In this paper, we jointly address the handover and beamforming challenges. In the next subsection, we describe our main contributions.

A. Our Contributions

The main objective of this paper is to develop an efficient and lightweight joint handover and beamforming method that maintains a predefined level of throughput on the UE’s trajectory. More specifically, we address the following questions.

• How to use sparsity and correlation of valid paths between the BS and the user equipment (UE) to design an efficient beamforming? We propose a beamforming algorithm based on constructing and maintaining a database of path skeletons, i.e., available paths between the BS and the UE. In our proposed algorithm, beam searching will only run through the path skeletons not through all the directions. Moreover, our algorithm tracks the correlation between path skeletons in different locations of the UE and queries a new path skeleton only when a significant change such as a sudden blockage has occurred.

• How to design a handover method that provides a reliable connection in mobile scenarios? We propose a learning-based handover method based on keeping an updated backup channel for the serving BS. We use reinforcement learning (RL) to optimize the list of the backup BSs. Our method comprises two decision making phases. In the first phase, our algorithm makes a decision regarding pingiing a good backup BS. We model this selection process as an RL problem that takes the mobility prediction information as input and returns the best candidate BSs as the backup for a specific location. In the second decision making phase, our algorithm uses the channel estimation results of the both serving and backup BSs and makes the handover execution decision.

• What are the benefits of our proposed method? We compare our proposed approach with two commonly used baselines in the literature. We numerically compare the key performance indicators including number of handovers, connection reliability, instantaneous rate and trajectory rate of our approach with the baselines. The
results indicate that our proposed approach substantially outperforms the baselines in terms of trajectory rate and more importantly connection reliability throughout the trajectory.

- **What is the performance of our proposed method in a realistic channel model?** We use ray tracing with real building data map as the input. We also add common blockages like human bodies and cars to the simulation area in order to evaluate the performance of our method in a more realistic environment.

We conclude that our solution is a signaling-efficient and lightweight approach that properly design the beamforming and handover so as to maintain a predefined quality-of-service level for the mmWave users in a dynamic and non-stationary environment. In the following, we will review state-of-the-art approaches for beamforming and handover in mmWave networks.

### B. Related works

Most of the mmWave beamforming approaches are carried out the exhaustive beam-searching over a set of pre-defined beams to find the beam pairs between a BS and a UE with the optimal alignment [8], [9]. However, due to the high dimension of the beam-searching, these approaches increase the overhead significantly. The authors in [10], [11] presented the beam-searching methods which used the sparsity and the correlation of spatial channel response of mmWave channels in adjacent locations. Despite of their promising results in terms of throughput, those methods are validated on stationary users [10] or increase the complexity of the beam-searching phase [11] thereby, constraining their applicability in real mobile scenarios. While in this work, we propose an efficient beamforming method for a mobile scenario and show that the complexity of our method is almost negligible in a crowded urban environment.

When it comes to the design of efficient and robust handover algorithms, the related state of the works can be grouped in three categories: learning-based handover [12]–[16], side information [15]–[20], and multi-connectivity [21]–[24].

To make the optimal handover decision, leveraging machine learning as the main decision maker tool can be an effective approach. In [12], authors used Markov decision process (MDP) in order to maximize the throughput and the achieved rate. Although the MDP optimal policy can reach the maximum throughput with the low number of handovers, due to the computation complexity of solving MDP, it cannot be applied to dense networks. The authors in [13] proposed a novel handover policy based on reinforcement learning (RL) for the radio access network slicing. The authors in [14] introduced an RL-based handover policy to reduce the number of the handovers while keeping the UE’s quality-of-service in the heterogeneous network. Although their promising results, they did not consider the channel estimation overhead in their approach. While in this work, we jointly consider the beamforming and handover problems. The authors in [15], [16] used the camera information to estimate the location of different obstacles and presented a proactive learning-based handover policy. However, due to the high density and variety of the obstacles in the urban environment, estimating the location of all obstacles may increase the network overhead. Our proposed learning-based handover method does not need online tracking of the obstacles and with keeping the connection toward a backup BS makes the handover decision.

Side information or context-aware aided approaches make use of the location of the user or the obstacles in order to make a handover decision. The work in [17] showed the importance of the location information in scaling mmWave networks to the dense and dynamic environment. Authors in [18] proposed a pose information assisted BS selecting mechanism to provide the mobility support and seamless coverage in mmWave networks. However, frequent changes of the UE’s field of view in a dynamic environment, challenges the applicability of the proposed approach in a real environment. In our proposed approach, besides the assumption of the availability of the side information (location of the user), we proposed a learning-based handover algorithm in order to provide a reliable connection which is more applicable to the real mobile scenarios. Authors in [19] proposed a handover method which leverages channel measurement of dominant line-of-sight (LoS) path of serving BSs in order to estimate the LoS path properties of other BSs toward the UE and then ranks BSs based on predicted beam strength. However, this method may not be applicable in all scenarios because this method cannot estimate good non-LoS (NLoS) paths in a crowded environment. While our proposed approach considers all available paths in the path skeleton set of serving BS and backup BS toward the UE during the channel estimation phase and use the RL in order to select the backup channel.

In the multi-connectivity methods, a UE maintains its connection to multiple BSs (either at the mmWave or sub-6 GHz bands). Simultaneous connection of a UE with multiple BSs are analyzed vastly in [21]–[24] as a solution to the link failure and the throughput degradation in a dynamic environment. However, power consumption, synchronization and the necessity of frequent tracking are main challenges of multi-connectivity methods. For example, although different multi-connectivity schemes proposed in [21] may improve the session-level mmWave operation in a realistic environment, the presented schemes need additional connection-probe procedures and knowledge of the mmWave system state which add the overhead to the network. Our proposed approach is based on keeping UE’s connection toward a backup mmWave BS with minimum overhead during the channel estimation by sending pilot signals only through the path skeleton sets.

### C. Organization and Notations

The rest of the paper is organized as follows. We introduce our system model in Section II. Section III describes our beamforming method and handover algorithm. We model the problem of choosing backup BS as an RL problem in Section IV. The numerical results are presented in Section V. Finally, the paper is concluded in Section VI.

**Notations:** Matrices, vectors and scalars are denoted by bold upper-case (X), bold lower-case (x) and non-bold (x) letters,
respectively. The $\ell_2$-norm and conjugate transpose of a vector $x$ (or a matrix $X$) are $\|x\|$ and $x^H$, respectively. We define set $[M] = \{1, 2, \ldots, M\}$ for any integer $M$.

II. SYSTEM MODEL

In this section, we introduce our main assumptions and system model. Table I summarizes our main notations.

A. Channel Model

We consider the downlink of a mmWave network with multiple BSs and mobile UEs. We assume a two-dimensional Poisson point process (PPP) with density $\lambda$ for the spatial distributions of the BSs, though our proposed algorithmic framework can work for any other model. We assume that a BS serves one UE. Extension to the multiple UEs scenario and load balancing at the BS are left for the future work.

We employ a geometric channel model [25] with sparse number of clusters and $N_{\text{BS}}$ antennas at the BSs and $N_{\text{UE}}$ antennas at the UEs with uniform linear antenna pattern. In this model the channel matrix $H \in \mathbb{C}^{N_{\text{UE}} \times N_{\text{BS}}}$ between $j$-th BS ($\text{BS}_j$) and a UE in location $i$ ($\text{UE}_i$) during a coherent interval (CI) $k$ is defined as:

$$H_{ji} = \frac{1}{\sqrt{\ell(d)}} \sum_{p=1}^{P} h_{j,i,p} a_{\text{UE}}(\theta_{j,i,p}) a_{\text{BS}}^{H}(\phi_{j,i,p}),$$

where $h_{j,i,p}$ is the unit-mean Rayleigh fading of $p$-th path between the $j$-th BS and the UE in location $i$ denoting small scale fading. Other realistic small scale fading models such as Nakagami provides the same design insight as Rayleigh model [26, 27]. $P$ is the number of paths, including LoS and NLoS, between $j$-th BS and the UE in location $i$. $\ell(d)$ is the path loss and $\phi_{j,i,p} \in [0, 2\pi)$ and $\theta_{j,i,p} \in [0, 2\pi)$ are the angle of departure (AoD) and the angle of arrival (AoA) of the $p$-th path from $j$-th BS to the UE in location $i$, respectively.

For a uniform linear antenna array with a spatial angle $\omega = \pi \sin(\varphi)$ and half-wavelength inter-element distance ($\lambda_c/2$), the antenna array response is:

$$a_s(\varphi) = [1, e^{-j\omega}, e^{-j2\omega}, \ldots, e^{-j(s-1)\omega}],$$

where $s \in \{N_{\text{BS}}, N_{\text{UE}}\}$ and $\varphi$ can be denoted by AoA ($\theta$) or AoD ($\phi$).

To model blockage in the geometric channel model, we consider a stochastic exponential blockage that approximates obstacles by rectangle Boolean objects [28]. In this model, the probability of having a LoS path between a UE and a BS is $p_{\text{LoS}}(d) = e^{-d\zeta}$ where $\zeta$ is a constant parameter that depends on the density and average size of the obstacles, $1/\zeta$ is the average length of a LoS link in the network, and $d$ is the distance between the UE and the BS. According to this model, the NLoS events on different links are independent.

For a given $p_{\text{LoS}}(d)$, the path loss for a path with length $d$ is

$$\ell(d) = \begin{cases} C_{\text{LoS}} d^{-\alpha_{\text{LoS}}} + X_{\text{LoS}} & \text{w.p. } p_{\text{LoS}}(d) \\ C_{\text{NLoS}} d^{-\alpha_{\text{NLoS}}} + X_{\text{NLoS}} & \text{w.p. } 1 - p_{\text{LoS}}(d) \end{cases},$$

where $\alpha_{\text{LoS}}$ and $\alpha_{\text{NLoS}}$ are the LoS and NLoS path loss exponents, respectively. $C_{\text{LoS}}$ and $C_{\text{NLoS}}$ are intercept parameters that can be assumed to be equal for LoS and NLoS paths when the reference distance is equal to one ($d_0 = 1$) [29]. We consider shadowing $X_d$ as a log-normal random variable with standard deviation $\mu_{\text{LoS}}$ and $\mu_{\text{NLoS}}$ for LoS and NLoS links, respectively [29 Table V].

The signal to noise ratio (SNR) at the UE in location $i$ from $j$-th BS can be defined as

$$\text{SNR}_{ij} = \frac{\|\mathbf{w}^{H} \mathbf{H}_{ji} \|^{2}}{\sigma^{2}},$$

where $\mathbf{f}$ is the beamforming vector in the BS side, $\mathbf{w}$ is the combining vector in the UE side, and $\sigma^2$ is the noise power which is normalized by transmit power. Due to the noisy dominant nature of highly directional mmWave transmission [25], we omit the interference effect of other BSs.

The main objective of designing beamforming and combining vectors is to maximize the link budget or SNR. With the small number of scatters in the environment, it is possible to design efficient beam-searching methods to adjust the array response [2]. For analytical tractability, we approximate the antenna response by a step function that is equal to a (usually big) constant value for the main beam and a small constant outside it [30]. The achieved rate per second is $R = W \log(1 + \text{SNR})$ where $W$ is the data transmission bandwidth.

In order to find the available paths between the $j$-th BS and the UE in location $i$, we define a set of path skeletons, $PS_{j,i} = \{p_1, \ldots, p_P\}$ with size $P$. Each path $p = \{\theta, \phi, \varphi\}$ is defined based on AoA ($\theta$) ,AoD ($\phi$) and the channel

| Table I: Nomenclatures. |
|--------------------------|
| **Notation** | **Description** |
| $j, N$ | Index and total number of BSs in a zone |
| $i, M$ | Location index and the length of a trajectory |
| $p, P$ | Index and total number of paths in a PS set |
| $\ell, L$ | Index and total number of SNR levels |
| SNR | Signal to noise ratio |
| PS | Path skeleton set |
| $f, w$ | Beamforming and combining vectors |
| $\sigma^2$ | Thermal noise power |
| $W$ | Signal bandwidth |
| $H_{\text{BS}}(\phi), a_{\text{UE}}(\theta)$ | Array response of BS and UE |
| $\phi_p, \theta_p$ | AoA and AoD of $p$-th path |
| $h_{p, \varphi}$ | Small scale fading and channel gain of $p$-th path |
| $N_{\text{BS}}, N_{\text{UE}}$ | Number of BS and UE antennas |
| $\alpha_{\text{LoS}}, \alpha_{\text{NLoS}}$ | LoS path loss exponent, NLoS path loss exponent |
| $L$ | A BS serves one UE. Extension to the multiple UEs scenario can work for any other model. We assume that a BS serves one UE. Extension to the multiple UEs scenario and load balancing at the BS are left for the future work. |
| $d$ | Distance |
| $\xi$ | Blockage exponent |
| $\nu_0$ | Serving and backup BS in CI $k$ |
| $\text{SNR}_{(\text{BS}_k, \text{BS}_j), (i, i)}$ | SNR level $r$ from BS$_k$ toward UE in location $i$ |
| $\eta_0$ | Age of the SNR in terms of CI |
| $\gamma_{\text{HO}}$ | Handover threshold |
| $T_{\text{D}}$ | PS distance threshold |
| $T_{\text{Aging}}$ | Aging threshold of a PS in the database |
Our proposed handover mechanism consists of three components: pilot design and channel estimation, mobility prediction, and handover algorithm. We first design the pilot signals and then estimate the channel toward the serving BS using those pilots, where \( P \) pilots, where \( P \) is the size of the path skeletons. We consider two decision making (DM) phases. In DM1, a backup BS for CI \( k \) will be determined based on the optimal policy of the RL algorithm and in DM2, the decision regarding the execution of the handover will be made. We define an acceptable handover threshold (\( T_{\text{HO}} \)) based on the user quality-of-service. In other words, during the DM2 if the channel quality of the serving BS becomes lower than the predefined \( T_{\text{HO}} \) for a certain duration (which can be defined based on UE’s quality-of-service), UE will switch to the backup BS. In the following, we will summarize our proposed efficient beamforming method, which we proposed in our recent work in [31].

In the channel estimation phase, we consider a path skeleton database in each BS that contains the path skeletons of different locations in the coverage area of every BS. However, having a path skeleton database entails two cost terms: query and maintenance. Query cost refers to the limited budget that BS can query a new path skeleton from the database and maintenance cost can be defined as the cost of building and keeping updated the database. First, we focus on the query cost and assume that an updated path skeleton database is available for all BSs. Then, we discuss the maintenance cost.

During the pilot transmission phase, the UE requests the path skeleton of its current location \((x, y)\), from the serving BS \( j \). The pilot sequences will be sent through the \( P \) paths of the \( PS_{j, l} \) in order to estimate the channel between the UE and BS. This estimation will then be used to design a precoding vector \( f \) at the BS (from a given codebook \( \mathcal{F} \)) and a combining vector \( w \) at the UE (from a given codebook \( \mathcal{W} \)) for the data transmission phase. Formally, we solve the following beamforming optimization problem:

\[
\begin{align*}
\text{maximize} & \quad |w^H H f|^2 \\
\text{subject to} & \quad f \in \mathcal{F}, \\
& \quad w \in \mathcal{W}.
\end{align*}
\]
In an environment with a small number of scatters, the optimal beamforming and combining may adjust to the array response of the strongest available path \[2\].

Due to the correlation of the path skeletons in adjacent locations \[31\], there is no need to query a new path skeleton in every location of the UE. In other words, the BS can track the path skeleton changes and only ask for a new beamforming solution when the current one is blocked or weakened by the obstacles. We consider the current path skeleton as the reference path skeleton when the current one is blocked or weakened by the obstacles. We define the distance between the reference path skeleton \(PS_i\) and estimated path skeleton in location \((x, y)\) \(j\) as a metric to assess the validity of using the reference path skeleton in the new location \((x, y)\):

\[
d(x_i, y_i; x_0, y_0) = ||PS_{j,i} - PS_{j,0}||_2. \tag{6}
\]

Observations of \[31\] show that once the distance is sufficiently close (namely \(d(x_i, y_i; x_0, y_0) \leq T_D \) for some small positive \(T_D\)), the UE can use the \(PS_{j,0}\) to estimate the channel \(H_{j,i}\) in new location \((x, y)\). Otherwise, the BS \(j\) declares a significant change in dominant paths. It then requires a new path skeleton and informs the UE. In this case, the reference path skeleton will be updated to the new path skeleton and the BS \(j\) tracks the validity of this new reference skeleton for beam-searching over time. We define \(T_D\) as the decision threshold that highly depends on the network topology. Smaller \(T_D\) will result in frequent updates of the path skeletons and higher throughput with a higher overhead cost. Larger \(T_D\) reduces the network overhead but may result in sub-optimal selected beamforming and combining directions through the UE trajectory.

In order to choose an optimal \(T_D\) for a limited query budget \((U_{\text{max}})\), we run our algorithm for different mobility models and trajectories in the coverage area of all BSs. For instance, in coverage area of BS \(j\), the optimal threshold \(T_D^*\) for pedestrian mobility model is the solution of the following optimization problem through a dataset of different pedestrian trajectories with different length \(M \in \mathbb{R}\):

\[
T_D^* = \arg\max_{T_D > 0} \sum_{i \in [M]} R_i, \tag{7a}
\]

subject to \(U < U_{\text{max}}\). \tag{7b}

This optimization problem is based on one-dimensional search over \(T_D > 0\) and can be solved numerically.

The efficiency of our proposed beamforming method can be defined based on four parameters: computational and signaling complexity, throughput efficiency and energy consumption. In terms of throughput, our approach guarantees a close-to-optimal performance by updating the beamforming and combining vectors. Moreover, by sending pilots only over the path skeletons, our approach substantially reduces the beam searching overhead (the number of beams required to find the best alignment), making it very efficient in terms of energy consumption, computational and signaling complexity.

Now, we present our approach regarding the building and maintaining the path skeleton database. In this case, we assume that every BS divides its coverage area to the small grids and assigns a unique ID to them. The size of all the grids is equal and is chosen based on the network topology and balancing the complexity of the building a database. Each grid is approximated to one point and one path skeleton is recorded for each grid ID in the database. In other words, only one path skeleton finding process (like the one in \[10\] or exhaustive beam-searching \[9\]) will run for each grid in order to build the path skeleton.

The path skeleton database has the normal list and the watch list that can be defined as the list of grid IDs with updated path skeletons and a list of grid IDs whose path skeletons need to be updated, respectively. As it is shown in Fig. 3 a BS sends the path skeleton finder request to the UE in every grid ID. It is important to note that a UE may refuse the request due to for example low battery level. If a UE accepts the request, the skeleton finder process will start and the skeleton is recorded.
in the normal list with a specific aging counter. If the aging counter of grid IDs in the normal list exceeds the predefined threshold (T_{\text{Aging}}), the BS will remove them from the normal list and adds them to the watch list. Fig. 3 illustrates this process.

T_{\text{Aging}} depends heavily on the network topology. In a crowded urban environment, the channel conditions will change rapidly so the database may need frequent updates. It means that T_{\text{Aging}} should be shorter for a highly dynamic environment compared to a stationary environment.

The overhead of the building and updating the database can be defined as the number of path skeleton finder requests that a UE will receive through its trajectory. In the crowded urban environment that the number of UEs is high, the database overhead is divided between all the users. Hence, the database overhead is almost negligible. More details of the proposed algorithm and performance evaluations are available in our recent work in [31].

### B. Mobility Prediction

The mobility behavior and localization of the UEs are the important challenges in communication networks due to the key applications in handover and resource management [32]. An accurate prediction of the mobility pattern in dense mobile networks can reduce the signaling overhead during the handover process [33, 34] and provide better quality-of-service and continuous connections.

As it is shown in [35], the mobility behavior of UEs in mmWave networks is predictable with good performance. Most of the mobility patterns like pedestrians or in vehicles are destination or direction oriented. The different mobility prediction schemes are in the literature use Markov chain, hidden Markov model, artificial neural networks, Bayesian network and data mining (for more details see [35]). The outputs of these prediction methods are the UE’s moving network and data mining (for more details see [35]). Studies in [17, 37] show that due to the use of the massive antenna arrays and the presence of the multi-path channel in mmWave networks, the performance of UE’s localization is sufficiently high in both uplink and downlink communication. In this work, we assume the mobility prediction information includes the user’s current location and its trajectory are available. The agent provides the mobility information to all BSs in its zone.

### C. Handover Algorithm

As mentioned in the previous subsection, the mobility prediction information, including UE’s trajectory with length M and its current location i ∈ [M], is the input to our proposed handover algorithm. We assume one agent for a zone with size of N where j ∈ [N] is the index of BSs.

We quantize the SNR_{(i,j),t} to L levels. During the channel estimation in both mini-slots S and B, we only report the SNR level SNR^{(p^*)}_{(i,j),t}, \ell \in [L], where p^* is the strongest path over PS_{j,i}, p^* = \text{argmax}_p h_{j,i,p} p \in PS_{j,i}. For the sake of notation simplicity, we drop the superscript of p^* and write SNR_{(i,j),t}. We define the handover threshold (T_{\text{HO}}) as the minimum acceptable SNR level. This parameter is determined based on the target quality-of-service level of the UE.

For our tagged UE, we let t_{\text{Log}} denote the age of the current SNR log toward BS_j in term of the number of CIs. The initial value of the t_{\text{Log}} for all BS\_j, j \in [N] is equal to t_{\text{Log}} = +\infty. Once SNR_{(j,i),t} is obtained for any i \in [M], t_{\text{Log}}(B_S) will be set to zero. At the end of each CI k, k \in \{1, 2, ..., \}, we add t_{\text{Log}}(B_S), \forall j \in [N] by 1 to indicate the age of the current log.

As it is illustrated in Algorithm 1 in the location i and CI k channel estimation toward the serving BS (B_{S,k}) and backup BS (B_{B,k}) starts during the mini-slot S and mini-slot B, respectively. If the SNR level of the B_{S,k} remains above T_{\text{HO}}, the serving BS in the next CI will not be changed; otherwise, the handover decision will be made during DM_2. If the SNR level of B_{S,k} drops lower than T_{\text{HO}}, for a certain time interval, the handover will be triggered. Then, a BS with an acceptable SNR (larger than T_{\text{HO}}) and a minimum amount of t_{\text{Log}} (the most recent SNR updated) will be selected as the main candidate for the handover. If multiple BSs meet this condition, we randomly select one.

**Illustrative Example 1:** Consider a zone with four BSs. The SNR is quantized to two levels \{t_1, t_2\} and T_{\text{HO}} is equal to

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**Algorithm 1 Handover.**

**Inputs:** User’s mobility model including current location i and trajectory i ∈ [M], number of BSs in the UE’s zone (N) and handover threshold (T_{\text{HO}}).

1. Initialization: For k = 1 set BS_{S,k} = BS_1
2. t_{\text{Log}}(B_{S,j}) = +\infty, for all j \in [N]
3. for i = 1, ..., M do
   4. for each CI k ∈ \{1, 2, ..., \} do
      5. // During mini-time slot S
      6. Estimate channel from BS_{S,i} toward location i and calculate the SNR_{(BS_{S,i})}
      7. Set t_{\text{Log}}(BS_{S,i}) = 0
      8. // During mini-time slot B
      9. Choose BS_{B,j} = BS_{j}, j \in [N] based on DM_1
   10. Estimate channel from BS_{B,i} toward location i and calculate the SNR_{(BS_{B,i})}
   11. Set t_{\text{Log}}(BS_{B,i}) = 0
   12. if SNR_{(BS_{S,i})} \geq T_{\text{HO}} then
   13. \quad BS_{S,k+1} = BS_{S,k}
   14. else
   15. \quad BS_{S,k+1} = BS_{B,k}
   16. // Perform handover
   17. if SNR_{(BS_{B,i})} > T_{\text{HO}} then
   18. \quad BS_{B,k+1} = BS_{B,k}
   19. else
   20. \quad BS_{B,k+1} = BS_{j}, where
   21. \quad j = \text{argmin}_j t_{\text{Log}}(BS_{j}) \text{ s.t. } SNR_{(j,i),t} > T_{\text{HO}}
   22. end if
   23. end if
   24. end if
   25. t_{\text{Log}}(BS_{j}) = t_{\text{Log}}(BS_{j}) + 1, \quad \forall j \in [N]
   26. end for
   27. end for
28. **Outputs:** BS_{S,k} and R_{i} for all i \in [M]
An initial value $Q(s,a)\forall s \in S, \forall a \in \mathcal{A}(s)$.

1: Initialization: An initial value $Q(s,a)\forall s \in S, \forall a \in \mathcal{A}(s)$

2: for each state $i \in [M]$ do

3: Observe $s_i$

4: Take a random variable $\rho$ uniformly from $[0,1]$

5: if $\rho \leq \epsilon$ then

6: Take a random action $a_i$ uniformly from set $\mathcal{A}(s)$

7: else

8: Take action $a_i = \arg\max_{a \in \mathcal{A}(s)} Q(s,a)$

9: end if

10: Observe $s_{i+1}$ and $r(s_{i+1},a_i,s_i)$

11: Update the action-value function as:

$$Q(s_{i+1},a_i) \leftarrow Q(s_{i+1},a_i) + \alpha (r(s_{i+1},a_i,s_i) + \gamma \max_{a \in \mathcal{A}(s_{i+1})} Q(s_{i+1},a) - Q(s_{i+1},a_i))$$

13: end for

The performance of the proposed handover approach heavily depends on how to select a backup BS for the mini-slot $B$ in various CIs. This selection depends on the predictions of the SNR values and blockage of the BSs in multiple future CIs. Such predictions, however, require a very detailed modeling of formidable complexity due to the dynamism of the obstacles and the UE mobility in mmWave networks. To address this problem, we use an RL framework to optimize the list of the backup BSs in various CIs.

An RL problem consists of a set of environment states $S$, a set of actions $\mathcal{A}(s)$, transition probabilities that model the SNR variations due to the UE’s mobility through its trajectory and obstacle topology, and a set of rewards $\mathcal{R} \subset \mathbb{R}$ [38]. The agent is the decision maker (which can sit in the edge cloud) based on the policy. More details regarding RL components are reported in Appendix A.

As it is shown in Fig. 4 all the BSs in a zone connect to the agent. We define states as tuple $s = (s^{(1)},s^{(2)},s^{(3)}) \in S$ where $s^{(1)} \in [M]$ is the current location of the UE through the trajectory with length $M$. $s^{(2)} \in [N]$ is the index of BSs in the zone and $s^{(3)} \in [L]$ is the quantized SNR levels. The agent’s action is choosing a BS in order to ping as the backup BS in mini-slot $B$.

We define the instantaneous reward as UE’s achieved rate in each location ($R_i$) and the long-term reward as the UE’s trajectory rate ($R_{\text{traj}}$)

$$R_{\text{traj}} = \sum_{i=1}^{M} R_i.$$ (8)

In each state $i$, we define the reward of choosing a backup BS (through action $a_i$) as a convex combination of the achieved rate from serving BS ($R^S$) and achieved rate of chosen backup BS ($R^B$).

$$r(s_{i+1},a_i,s_i) = \beta R^S_i + (1-\beta)R^B_i.$$ (9)

where $\beta \in [0,1]$ is a scalar to tradeoff the current rate or the potential one after handover. We set $\beta$ to be close to one. In summary, $r(s_{i+1},a_i,s_i)$ is a reward that agent received in state $s_{i+1}$ because of its action $a_i$ in state $s_i$.

The aim of the RL algorithm is to find an optimal policy ($\pi^*$) that maximizes UE’s achieved rate through its trajectory. In our case matrix $\pi^*$ consists of $M$ columns and $N$ rows. It shows the best choice of backup BS in each location of the trajectory. In other words, the first element of each column shows the best choice of backup BS for each location of the UE’s trajectory. When a link is about to be failed, the agent chooses the BS with high probability (the first element of each row) in matrix $\pi^*$ based on UE’s current location. The $\pi^*$ can be defined as:

$$\pi^* = \arg\max_{\pi} \mathbb{E}[R_{\text{traj}}],$$ (10)

where the expectation is with respect to the randomness in the channel gain and obstacle process.

In order to find $\pi^*$, we use Q-learning algorithm, which enables learning with no prior knowledge of the environment and finds the optimal decision based on the interactions with the environment, using Algorithm 2 [38]. In Appendix B, we have provided more detailed information on the Q-learning and how it works.

V. SIMULATION RESULTS

In this section, we present the simulation results of running our proposed method in two parts. In the first part, we use geometric channel model with different BS densities and in the second part, we use ray tracing tool to simulate a more realistic blockage and mmWave channel model. In all simulations, we fix the UE’s trajectory. We consider a zone of $100 \times 100$ m$^2$ area. The topology and the trajectories are shown in Fig. 4.

The simulation parameters are listed in Table 1.

We compare the performance of our proposed method with two baselines: random-backup handover [21] and no-backup handover [8]. In the random-backup handover baseline, we assume that in each CI a backup BS will be chosen randomly from the BSs in the zone. In the no-backup handover, we assume that a UE only keeps its connection toward its serving BS. If the current link quality drops bellow than the predefined
handover threshold, the UE starts a new connection with the strongest BS after an exhaustive search over all BSs in the zone.

A. Geometric Channel Model

We first assume a geometric channel model for a UE with a trajectory of 100 m. We consider two mobility models in our numerical studies: pedestrian and vehicle, where we assumed a UE speed of 5 km/h and 36 km/h, respectively. Due to the similarity of the results, we only report the pedestrian mobility model in the following.

We use $10^4$ different channel realizations as the input of the RL algorithm. During the learning phase, we run our algorithm in order to reach the optimal policy that in this case is the optimal backup BS in different UE’s locations. Based on the speed of the pedestrian, we define location indexes every 2 m (50 location indexes through the trajectory). We run two different scenarios with different BS densities as follows:

1) First Scenario (sparse mmWave network): In the first scenario, we consider a BS density of $\lambda = 5 \times 10^{-4}/m^2$, which corresponds to the average of one BS in every 50 $m^2$. After getting the optimal policy, we run our proposed algorithm over $10^6$ different channel realizations. Figure 5 compares the performance of our approach to the baselines. In particular, Fig. 5a shows the probability density function of the number of handovers when the UE moves along with the trajectory, Fig. 5b shows the average $R_i$, $i \in [100]$ per location, and Fig. 5c shows the average $R_{\text{traj}}$. It is evident from the figure that our learning-based handover method with reducing the rate fluctuations through the UE’s trajectory is more reliable handover method specially in high quality-of-service cases. Furthermore, our method keeps the minimum number of handovers and an on-demand exhaustive search adds latency and a noticeable service disruption, as can be observed in Fig. 5a.

2) Second Scenario (dense mmWave network): In the second scenario, the density of the BSs is $\lambda = 10^{-3}/m^2$ which corresponds to the average of one BS in every 30 $m^2$. Fig. 6 illustrates the probability density function of the number of the handovers, $R_i$, $i \in [100]$ and $R_{\text{traj}}$. It is evident that our learning-based handover method with reducing the rate fluctuations through the UE’s trajectory is more reliable handover method specially in high quality-of-service cases. Furthermore, our method keeps the minimum number of handovers.

In our case, in order to get the learning convergence, we run our algorithm $10^6$ times. The running time by using a standard desktop computer is around 30 minutes.
Table II: Simulation parameters.

| Parameters                                | Values in Simulations |
|-------------------------------------------|-----------------------|
| BS transmit power                         | 30 dB                 |
| Thermal noise power                       | $\sigma^2=-174$ dB/Hz |
| Signal bandwidth                          | $W=500$ MHz           |
| Operation frequency                       | 28 GHz                |
| Number of BS antennas                     | $N_{BS}=16$           |
| Number of UE antennas                     | $N_{UE}=16$           |
| Geometric channel parameters              |                       |
| LoS path loss exponent                    | $\alpha_{LoS}=3$      |
| NLoS path loss exponent                   | $\alpha_{NLoS}=4$     |
| Blockage exponent                         | $\zeta=0.04$          |
| Ray tracing parameters                    |                       |
| BS height                                 | 6 m                   |
| Brick penetration loss                     | 28.3 dB               |
| Glass penetration loss                     | 3.9 dB                |
| Handover and learning parameters          |                       |
| Handover threshold                        | $T_{HO}=0$ dB         |
| Learning rate                             | $\alpha=0.1$         |
| Discount factor                           | $\gamma=0.99$        |
| Exploration rate                          | $\epsilon=0.01$      |
| Reward rate                               | $\beta=0.8$          |

Fig. 6: Handover performance of our approach compared to baselines for simulated data in a dense mmWave network.

handover needed while providing comparable $R_i$ and $R_{traj}$ to the other two baselines.

B. Ray Tracing

We have also used ray tracing to model and evaluate the performance of our approach in a more realistic environment. For the network topology, we extracted the real building map of the central part of Stockholm city as the input of the ray tracing tool [40]. Then, we randomly assigned brick or glass materials to the buildings as the permanent obstacles. We also added some temporary random obstacles with heights 1.5 m to model human bodies and some temporary random obstacles with width 4 m and heights 1 m and 3 m to model various vehicles with different heights. The number, the position and the material loss of the temporary obstacles were chosen randomly in each realization of the channel. The simulation area is illustrated in Fig. 4. We placed the UE’s trajectory with length 100 m and the vehicle mobility model. We consider the location indexes every 10 m (11 location indexes through the trajectory) as is shown with the blue line in Fig. 4. The density of the BSs is $\lambda = 5 \times 10^{-4}$/m$^2$.

We run the ray tracing simulator for all the BSs for different topologies. We considered each topology with different distribution and density of the temporary obstacles.

As it is evident from Fig. 7 our proposed solution needs minimum numbers of the handover while keeping the $R_i$ consistent in all the locations of the trajectory. It is evident that the other two baselines cause high rate fluctuations in many locations of the UE.

VI. Conclusions

In this paper, we jointly considered the beamforming and handover challenges in mobile mmWave networks. We proposed an efficient beamforming method which leverages the sparsity and the spatial correlation of path skeletons in the channel estimation phase. We designed a handover algorithm based on a pilot structure that consists of an extra mini-slot regarding channel estimation toward backup BS. We used reinforcement learning algorithm as a decision maker regarding the choice of the backup BS in all locations of the UE’s trajectory. Our proposed algorithm triggers a handover to a backup channel when the link quality drops below a predefined threshold. We evaluated the performance of our method based on the geometric channel model and ray tracing. The results showed that our approach provides a reliable connection with the consistent rate through the UE’s trajectory.

For future work, we plan to extend our joint beamforming and handover approach to multi-user scenario and take the load balancing and resource management of the BSs into account.
reward of its action in the previous step. The agent and environment will interact with each other in all the steps in order to complete the knowledge of the agent about different states of the environment. The main goal of the agent in RL is learning the optimal policy $\pi^*$ in order to maximize its long-term rewards. In particular, the agent maximizes the expected discount reward and finds the optimal policy as [38]:

$$\pi^* = \arg\max_{\pi} E_{\pi} \left[ \sum_{i=0}^{\infty} \gamma^i r_{i+1} | s_i = s \right],$$

(11)

where $r_{i+1} = r(s_{i+1}, a_{i+1}, s_{i+1})$ is a reward that agent received in state $s_{i+1}$ because of its action $a_{i+1}$ in state $s_i$ and $\gamma \in [0, 1]$ is the discount factor. The expectation is with respect to the randomness in policies.

In episodic learning, the interaction between agent and environment breaks into subsequences which are called episodes [38]. Each episode has a limited number of states. In our scenario, every running of a fixed trajectory with a random distribution of the temporary obstacles can be considered as an episode with the length $M$ where $M$ is the length of the trajectory.

APPENDIX B
Q-LEARNING

The optimal action-value function $Q^*(s, a)$ can be defined as:

$$Q^*(s, a) = \arg\max_{\pi} E_{\pi} \left[ \sum_{i=0}^{M} \gamma^i r_{i+1} | s_i = s \right].$$

(12)

where the expectation is over random policies. The optimal policy $\pi^*$ of the agent is a policy which by taking that action, the action-value function is maximized that can be defined as:

$$\pi^*(s) = \arg\max_{a \in \mathcal{A}(s)} Q^*(s, a) \quad \forall s \in \mathcal{S},$$

(13)

Based on Q-learning in $\epsilon$-greedy policy, agent takes action $a_i = \arg\max_{a \in \mathcal{A}(s)} Q^*(s, a)$ in state $s_i \in \mathcal{S}$ with probability $1 - \epsilon$ where $\epsilon \in [0, 1]$ in each step $i$. In next state $s_{i+1} \in \mathcal{S}$, agent observes the reward on taking action in the previous state $s_i$ and updates the optimal action-value function [38].

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Moreover, we plan to work on an accurate mobility prediction scheme using the tracking and localization capabilities of the mmWave networks.

APPENDIX A
REINFORCEMENT LEARNING

In this part, we introduce the reinforcement learning (RL) model as a decision making tool.

At each step $i$ for $i \in \{M\}$, the agent makes a decision regarding a new action based on the immediate received reward of its action in the previous step. The agent and environment will interact with each other in all the steps in order to complete the knowledge of the agent about different states of the environment.
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