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# Deep Reinforcement Learning for Dynamic Band Switch in Cellular-Connected UAV

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**Abstract**—The choice of the transmitting frequency to provide cellular-connected Unmanned Aerial Vehicle (UAV) reliable connectivity and mobility support introduces several challenges. Conventional sub-6 GHz networks are optimized for ground Users (UEs). Operating at the millimeter Wave (mmWave) band would provide high-capacity but highly intermittent links. To reach the destination while minimizing a weighted function of traveling time and number of radio failures, we propose in this paper a UAV joint trajectory and band switch approach. By leveraging Double Deep Q-Learning we develop two different approaches to learn a trajectory besides managing the band switch. A first blind approach switches the band along the trajectory anytime the UAV-UE throughput is below a predefined threshold. In addition, we propose a smart approach for simultaneous learning-based path planning of UAV and band switch. The two approaches are compared with an optimal band switch strategy in terms of radio failure and band switches for different thresholds. Results reveal that the smart approach is able in a high threshold regime to reduce the number of radio failures and band switches while reaching the desired destination.

**Index Terms**—UAV, UE, trajectory, Deep Reinforcement Learning, cellular network, sub-6 GHz, mmWave

## I. INTRODUCTION

Integrating Unmanned Aerial Vehicles (UAVs) into cellular communication systems as User Equipments (UEs) is envisioned as an effective solution to support the UAV's mission specific rate-demanding data communication while improving the robustness of the UAV navigation [1]. This vision of cellular connected UAVs communication, however, poses new research challenges due to the significant differences from conventional communication systems. UAVs-UE have typically higher altitude, higher mobility and have more stringent constraints on the power and operational time than the corresponding ground ones [2]. In addition, the existing cellular network operating at sub-6 GHz is bandwidth limited and performs poorly at high UAV heights, due to the interference perceived from the down-tilted antennas at the ground Base Stations (BSs) [3]. As a consequence, during its trajectory, a UAV is very likely to experience radio link failures. The UAVs' mobility and flexibility offer a degree of freedom to circumvent these issues. The UAV path design that aims to respect a quality-of-connectivity constraint and minimize the travelling time goes under the name of *Communication-aware* trajectory. Several works have optimized the UAV trajectory under connectivity constraints using graph based [4] or dynamic programming based [5]

solutions. The above traditional optimization solutions are time consuming and computationally complex. For this reason, Reinforcement Learning (RL) approaches have been recently investigated. Compared to a traditional optimization approach, RL is able of making decisions interacting iteratively with the environment. A double Q-Learning approach is proposed in [6] to solve a joint trajectory and outage time constraint problem. A Temporal Difference (TD) learning method is utilized in [7] to design the UAV-UE trajectory while minimizing the mission completion time and the disconnection duration.

Besides, exploiting their mobility, UAVs can establish short Line of Sight (LoS) communication links, that represents an ideal situation to transmit at millimeter Wave (mmWave) band. A mmWave link offers a wide spectrum and enables the use of directional beamforming, providing high data rate [8]. The work in [8] addresses the cellular connected UAV communication-aware trajectory problem learning simultaneously the mmWave beam and trajectory via Deep Q-Network (DQN) to improve the Uplink (UL) performance. However, due to the severe attenuation and sensitivity to blockages, mmWave links are highly intermittent, leading to frequent radio failures at low UAV altitudes [9].

A promising solution to improve the system robustness is to support two different frequency ranges, leading to integrated dual mode sub-6 GHz/mmWave systems [10]. Dual connectivity would allow to exploit the complementary advantages of both the frequency bands and reduce consistently outage status through band switch algorithms. Some literature has recently studied the band switch problem for conventional ground UEs in a 2D environment. Works in [11]-[12] propose Machine Learning (ML) classifiers that select the best band based on previous rate measurements within a temporal window. Within the UAV communication context, in [13] UAVs are equipped with dual band mmWave and sub-6 GHz communication modules to act as relays to minimize the total service time, but the switch algorithm between the bands is not investigated.

In this paper, differently from previous works, we aim to solve the communication aware 3D trajectory problem of UAV-UE proposing a learning strategy to both manage the trajectory and the band switch policy. We firstly formulate a trajectory problem in order to minimize the travelling time and radio failures of the UAV. Then we propose a 3D DQN based algorithm to dynamically solve it adjusting the position and the operating frequency of the UAV-UE. Finally, we present

also a blind switch strategy and introduce a baseline optimal band switch policy. We compare the performance of these three approaches in term of number of radio failures and band switches in the result section. We observe that the smart approach significantly improves the performance of the ground BS link for stringent thresholds.

## II. SYSTEM MODEL

### A. Network Topology

Consider the downlink of a dual band wireless cellular network, that operates in two frequency bands with frequency  $f_c$  and bandwidth  $B_c$ ,  $c \in \{1, 2\}$ . A set of ground Distributed Units (DUs) is deployed in an area  $\mathcal{X} \in \mathbb{R}^3$ , connected to a single Centralized Unit (CU), and serve a set of  $N$  UAV-UEs. Both DUs and UEs are equipped with interfaces which allow them to transmit at both frequency bands. We assume the transmission occurs in a single frequency at a time, generating inter-cell interference to neighboring cells working at the same frequency band. Each DU is assumed to have  $n_b$  Resource Blocks (RBs) and transmits with same power  $P_{DU}^c$ . Without loss of generality, we focus on a single link to a UAV-UE (hereafter addressed as UAV).

### B. Ground-to-Air Channel Model

In this section we present the path loss, antenna and fading models, considering  $f_1$  a lower sub-6 GHz band and  $f_2$  the mmWave band.

1) *Path Loss and Antenna Model:* The ground-to-air channel model is subject to LoS/Non-Line of Sight (NLoS) variations based on the building distribution in  $\mathcal{X}$  and UAV height that lead to blockages. For modeling the path loss  $L^1(d)$  at sub-6 GHz we consider the urban Macro (UMa) path loss specified in 3rd Generation Partnership Project (3GPP) [14]. The path loss  $L^2(d)$  at mmWave follows a path loss model [9]:

$$L^2(d) = \begin{cases} L^L(d) = X_L d^{-\alpha_L}; \\ L^{NL}(d) = X_{NL} d^{-\alpha_{NL}}; \end{cases} \quad (1)$$

where  $d$  is the ground BS-UAV distance, parameters  $\alpha_L$ ,  $\alpha_{NL}$  and  $X_L$ ,  $X_{NL}$  represent, respectively, the path loss exponent for LoS/NLoS and the path loss at 1 meter distance. Each DU has three sectors separated by  $120^\circ$  as characterized by 3GPP specification [14]. Each sector is equipped with a vertical  $N_1$ -element uniform linear array (ULA) at  $f_1$  and a Uniform Planar Array (UPA)  $N_2 \times N_2$  at  $f_2$  tilted with angle  $\phi_1$  and  $\phi_2$ . We denote the total ground DU directional radiation pattern as  $G(\Theta, \phi)$ , where  $\Theta$ ,  $\phi$  are elevation and azimuth angles. We assume the UAV is equipped with a conventional omnidirectional antenna of unitary gain in any direction to maintain low complexity and cost at the UAV.

2) *Fading Model:* We model the small scale fading fading power  $f_{0,i}^2$  with  $i \in \{LoS, NLoS\}$  as a Nakagami-m fading model, that covers a wide range of fading environments, including both sub-6 GHz ( $m = 1$ ) and mmWave ( $m = 3$ ). Accordingly,  $f_0^2$  follows a Gamma distribution with  $\mathbb{E}[f_0^2] = 1$ .

### C. UAV Mobility Model

The UAV moves at constant speed  $V = V_{max}$  along a 3D trajectory of duration  $T$  that can be divided into  $K$  discrete segments with interval  $\delta_k = T/K$ ,  $k = \{1, \dots, K\}$ .  $\delta_k$  is chosen arbitrarily small so that within each step the large scale signal power received by the UAV remains approximately unchanged. Each segment is thus described by its discrete coordinates  $\mathbf{q}_k = [x_k, y_k, h_k]$ . The trajectory of the UAV starts from a random position  $\mathbf{q}_I \in \mathcal{X}$  in the given area of interest  $\mathcal{X}$ , delimited by borders  $[x_{min}, x_{max}] \times [y_{min}, y_{max}]$  while the altitude of the UAV must satisfy  $h_k \in [h_{min}, h_{max}]$ , where  $h_{min}$  represents the lower bound of UAVs' altitude to avoid collisions and  $h_{max}$  represents the upper bound. The trajectory ends when the UAV reaches a final destination  $\mathbf{q}_F$ .

### D. Communication Model

The achievable rate  $R_A^c$  at  $\mathbf{q}_k$  in band  $c$  can be expressed as:  $R_A^c(\mathbf{q}_k) = B_c \mathbb{E}(\log_2(1 + SINR^c(\mathbf{q}_k)))$ , where  $B_c$  is the bandwidth assigned to the link and  $SINR^c$  the Signal-to-Noise-plus-Interference Ratio (SINR). At each trajectory step  $\mathbf{q}_k$ , the UAV associates with the  $m$ -th DU at position  $\mathbf{b}_m = [x_m, y_m, h_m]$  providing the highest average Reference Signals Received Power (RSRP) at the current frequency. Assuming that the associated cell remains unchanged within each trajectory step, the SINR at the UAV can be denoted as:

$$SINR^c(\mathbf{q}_k, m) = \frac{\gamma_m^c(k)}{\sigma^2 + \sum_{j \neq m} \gamma_j^c(k)}, \quad (2)$$

where  $\gamma_m^c(k)$  is the received power  $\gamma_m^c(k) = P_{DU} L^c(\|\mathbf{b}_m - \mathbf{q}_k\|_2) f_0^2(\mathbf{q}_k) G(\Theta, \phi)$  and terms in the denominator are, respectively, the spectral noise and the interference. Note that a subscript to emphasize the  $\{LoS, NLoS\}$  dependence of  $L()$  and  $f$  has been omitted to lighten the notation.

To maintain a reliable connection, DU-UAV link must satisfy a rate threshold  $R_{TH}$ . We define a *radio failure* on the link if  $R_A^c(\mathbf{q}_k) < R_{TH}$  occurs at step  $k$ . In addition, we introduce a failure indicator as:

$$F(\mathbf{q}_k) = \begin{cases} 1, & \text{if } R_A^c(\mathbf{q}_k) < R_{TH} \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

To avoid a radio failure, at each discrete step  $k$  the UAV may require the CU a band switch to change the transmission frequency. Prior to formulating the problem, in what follows we introduce the band switch procedure and signalling.

### E. Band switch procedure

The band switch policy industry standard for a conventional ground UE is composed of several iterative steps which can be summarized as follows : 1) if the serving rate  $R_A^c$  at current frequency drops below threshold  $R_{TH}$ , the UE initiates a band switch procedure with the serving cell, 2) the UE utilizes a time  $\Delta_t$  to measure if a cell at target frequency offers a higher RSRP than the serving cell, 4) if yes, the UE triggers a band switch procedure and reports the measurement back to the DU, 5) the CU makes a decision on the suitable DU at target

frequency for band switch, based on the UE measurements. Applying the above policy to UAV communications would introduce several challenges. The mobility of the UAV might cause deep RSRP fluctuations between two consequent trajectory steps  $\mathbf{q}_k$  and  $\mathbf{q}_{k+1}$ . This might lead to subsequent band switch procedures and potential ping-pong effect. Note that, due to the measurement gap, in case of several band switches the effective throughput at the UE suffers a significant reduction [12]. Thus, we modify the above band switch procedure to adapt it for a UAV moving between cells belonging to different DUs controlled by a central CU. Here, motivated by the above mentioned challenges, we formulate a real-time trajectory and band switch procedure exploiting the capabilities of a RL based policy. In the next sections we formulate the problem and propose two DQN algorithms for joint UAV-UE trajectory and band switch.

### F. Problem formulation

The goal of the UAV is to reach the destination in the minimum amount of steps while minimizing the number of radio failures. At the same time, to avoid a radio failure and meet the quality of service requirement, at the beginning of each discrete step  $k$ , the operating frequency can be switched between  $f_1$  and  $f_2$ . Denoting as  $K$  the trajectory steps,  $N_s$  the number of band switches, the above problem can be mathematically formulated as:

$$\min_{N_s, K, \mathbf{q}_k} \quad \kappa_1 \sum_{k=1}^K F(\mathbf{q}_k) + \kappa_2 K + \kappa_3 N_s \quad (4a)$$

$$\text{s.t.} \quad \mathbf{q}_0 = q_I, \quad (4b)$$

$$\mathbf{q}_K = q_F, \quad (4c)$$

where  $\kappa_1, \kappa_2, \kappa_3$  weight the summation of the arguments, (4b), (4c) are the starting and final positions. Problem (4) cannot be readily handled by conventional optimization methods due to the non trivial design of  $R_A^c(\mathbf{q}_k)$ , function for each position of the fading, and the antenna model described in Section II.

To tackle this challenging problem, we propose a novel approach by leveraging the DQN technique. DQN based frameworks are able to solve the joint trajectory and band switching problem by exploring different actions, and without the need of prior knowledge or predefined dataset to train the network.

## III. BAND SWITCHING AS A DEEP REINFORCEMENT LEARNING PROBLEM

In the standard RL setting an agent acts in an environment over discrete time steps. Given that problem (4) has been formulated in a discrete form, we can directly map it into a Markov Decision Process (MDP) 5-tuple  $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$ , with space state  $\mathcal{S}$ , action space  $\mathcal{A}$ , state transition probability  $\mathcal{P}(s'|s, a)$ , reward function  $\mathcal{R}(s, a, s')$ , and discount factor  $\gamma \in [0, 1)$ . At each time step  $k$ , the agent receives an observation  $o_k$  and selects an action  $a_k$ , receives reward  $r_{k+1}$  from the environment and goes from state  $s_k$  to a new state

$s_{k+1}$  where the cycle restart. We assume an episodic setup, where an episode starts with time step 0 and concludes with time step  $K$ . Here the states consist in the 3D location of the UAV  $\mathbf{q}_k$  and band switch indicator  $w_k \in \{0, 1\}$ , such as  $s_k = \{\mathbf{q}_k, w_k\} \in \mathcal{S}$ . Both the location and the band switch indicator are the input of the neural network. The agent, placed at the CU to overcome the limited onboard computing capacity, selects an action in a set of  $N$  actions  $\{a_1, \dots, a_N\}$  in the action space  $\mathcal{A}$ . The action can be represented by parameters  $a_k = \{\eta_k, w_k\}$  where  $\eta_k$  corresponds to the movements of the UAV in altitude (up or down) or in the horizontal direction (left-right-forward-back). In addition, if  $w_k$  is positive, the CU triggers a band switch in the network operating frequency without a measurement gap. Based on the selected action the UAV moves in the desired direction for a distance  $\delta_k$  at speed  $V_{max}$  reaching the position  $\mathbf{q}_{k+1}$ . Our goal is to predict the UAV direction along with the transmitting frequency to avoid radio failures and reach the destination using the current rate measurement. With this aim we define as reward function as:  $r_k = \lambda_1 \mathcal{F}_1 + \lambda_2 \mathcal{F}_2 + \lambda_3 \mathcal{F}_3$ .  $\mathcal{F}_1$  is a negative cost and forces the UAV to reach the destination in the minimum amount of steps.  $\mathcal{F}_2$  denotes the cost for entering in low normalized rate regions ( $R_{TH}/R_A^c(\mathbf{q}_k)$ ), that lead to radio failures.  $\mathcal{F}_3$  accounts for the band switches occurred until time step  $k$ . Note that  $\mathcal{F}_3$  is a cost since a high number of band switches is not desirable. Thus,  $\lambda_1, \lambda_2, \lambda_3$  balance the impact of the three factors on the reward function and need to be properly adjusted.

In order to achieve the desired goal, we need to find a policy that maximizes the long-term average of both connectivity and path guidance. We recall that a policy  $\pi(s_k, a_k)$  is defined as the probability of taking action  $a_k = a$  in state  $s_k = s$ , through interacting with the environment. Based on this, the problem is equivalent to find a policy  $\pi(s_k, a_k)$  that maximizes a cumulative discounted reward over the long run:

$$G_k = \sum_{i=0}^{K-1} \gamma^i r_{k+i+1}. \quad (5)$$

The discount factor  $\gamma$  in (5) regulates the relative importance of future and immediate rewards.

After being formulated as an MDP, Problem (4) can now be solved via different RL algorithms.

### A. DDQN for UAV-UE Trajectory and Smart Band Switch

In the convention RL approach, for a given policy  $\pi$ , a state-action function  $Q(s, a)$  is introduced to represent the expected return after taking action  $a_k$  in state  $s_k$ . In order to deal with large state/action space dimensions DQN was introduced in [15] to approximate the optimal Q-function using a Deep Neural Network (DNN) such that  $Q(s, a; \theta) \approx Q(s, a)$  where  $\theta$  are the network' weights. The transitions  $(s, a, r, s')$ , with  $s' = s_{k+1}$  are stored into a memory of finite capacity size  $H$  and randomly picked when performing a Q-value update. At each iteration, DQN is trained to minimize the loss:

$$L(\theta) = E[(y_k - Q(s_k, a_k | \theta_k))^2] \quad (6)$$

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**ALGORITHM 1: DDQN Algorithm for Band Switch Trajectory**


---

```

1 Initialize: maximum number of episodes, the replay memory  $H$ 
  with capacity  $N$ , mini batch size  $B$ ;
2 the DQN  $Q$  network with coefficients  $\theta$ , the target network  $\tilde{Q}$  with
  coefficients  $\theta^- = \theta$ ;
3 Algorithm hyperparameters  $(\epsilon, \lambda_1, \lambda_2, \lambda_3, \gamma)$ , Rate Threshold  $R_{TH}$ ;
4 for  $episode = 1, \dots, \text{Max episode}$  do
5   Initialize  $q_0 = \{\mathbf{q}_I\} \in \mathcal{S}$ ,  $w = 0$ , set step  $k \leftarrow 0$ ;
6   for each step of episode do
7     if  $\text{rand}() < \epsilon$  then
8       select action  $a_k$  randomly;
9     else
10      choose action  $a_k = \arg \max Q(\mathbf{s}_k, a_k, \theta)$ 
11    end
12    end
13    Agent execute action  $a_k$ , observe  $\{\mathbf{q}_{k+1}, w_k\}$ ;
14    if  $w_k == 1$  then
15       $f_c = !f_c$  (Band Switch)
16    end
17    if Destination reached then
18      Terminate Episode;
19    end
20    Store transition  $\{\mathbf{s}_k, a_k, r_k, \mathbf{s}_{k+1}\}$  in  $H$ ;
21    Compute reward  $r_k$ ;
22    Randomly sample mini batch from replay memory  $H$ ;
23    Perform a gradient descent using (6) and (7);
24    Update  $\tilde{Q} = Q$  every  $C$  steps;
25  end
26 end

```

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where  $y_k$  is the target function given by  $y_k = r_k + \gamma \max_a Q(s_{k+1}, a | \theta^-)$ , where  $\theta^-$  is introduced following the *target network mechanism*. We denote the primary DNN network weight matrix and target DNN weight matrix as  $\theta$  and  $\theta^-$ . We consider a fully connected DNN for both networks and the DNN parameters  $\theta^-$  are updated with the parameters  $\theta$  every fixed number of steps  $C$  to improve the convergence of the algorithm. Among the improvements and extensions of the baseline DQN algorithm, we implement Double DQN (DDQN) which reduces the overestimation bias of DQN with a simple modification of the update rule. In particular, the target function becomes:

$$y_k = r_k + \gamma \max_a Q(s_{k+1}, \arg \max Q(s_{k+1}, a_{k+1}, \theta_k), \theta_k^-). \quad (7)$$

In Algorithm (1) we introduce the complete pseudocode.

1) *Analysis of the Smart Switch Algorithm:* The proposed algorithm aims to solve the challenges of the state of the art band switch policy presented in Section II-E. After the initialization procedures, the agent performs an initial exploration of the state space through an  $\epsilon$ -greedy policy (lines (7 – 12) in Algorithm (1)). The UAV moves in a custom environment consisting of the area under consideration  $\mathcal{X}$  covered by the dual band network, the possible UAV locations and discrete action space. At each episode, the environment resets the source UAV location, computes new observations and rewards based on the desired action until it reaches destination. Since the band switch indicator is included as input state of the DNN, goal of the agent is to learn by experience in which states bandswitching is beneficial, without the need for measurement

Parameter	Description	Value
$h_{max}/h_{min}$	UAV Max/Min Height	120/60 m
$N_1/N_2 \times N_2$	Antenna Element $f_1/f_2$	8/64
$\phi_1/\phi_2$	Antenna Tilt $f_1/f_2$	-10/10 deg
$\sigma^2$	Noise Power $f_1/f_2$	-204/-120 db/Hz
$\delta_k$	time step length	0.5 s
$\epsilon$	$\epsilon$ -greedy variable	0.4
$K$	UAV Max Moves	200
$\gamma$	discount factor	1
$H$	Replay Memory Size	100000
$\lambda_1, \lambda_2, \lambda_3$	Rewards weights	0.1, 0.8, 0.1

TABLE (I) Simulation parameters

of gaps.

Next, we introduce a Blind DQN Algorithm for the joint UAV-UE Trajectory and Band Switch and an Optimal Algorithm.

### B. DDQN for joint UAV-UE Trajectory and Blind Band Switch

To solve the optimization problem (4) we propose also a Blind algorithm, that focuses on learning the best trajectory to reach the destination and switches the transmitting frequency any time a radio failure occurs. Differently from the Algorithm presented in Section III-A, the states consist of the 3D location of the UAV and the action in the direction only. In addition, in the reward function,  $F_3 = 0$ . The Algorithm pseudocode is omitted here since it is similar to the one presented in Algorithm 1. This band switch algorithm without information about the instantaneous rate at both frequencies, cannot guarantee that the throughput after the band switch will be higher than the original one.

### C. Optimal DDQN for UAV-UE Trajectory

Finally, as benchmark, we introduce an Optimal Algorithm. At each trajectory step  $\mathbf{q}_k$  the agent knows the instantaneous achievable rate of the two different bands. Therefore, the CU at each step coordinates the DUs to transmit at the best frequency, minimizing the radio failures due to a wrong choice about the band.

## IV. SIMULATION RESULTS

In this section we evaluate the performance of the proposed DQN algorithms and we benchmark them with the Optimal Policy. We consider a deployment of 5 dual band DUs in an area of side 2 km where buildings are modeled as for the ITU-R urban statistical model [16] with maximum height of 50m. The two frequency bands considered are  $f_1 = 2$  GHz and  $B_1 = 180$  kHz, and  $f_2 = 28$  GHz and  $B_2 = 1800$  kHz. We use one RB at sub-6 GHz while ten at mmWave [12]. We choose to transmit at 0.1 W at mmWave and at 1 W at sub-6 GHz. In the proposed DQN algorithms, the DNN consists of input layer, four hidden layers, one output layer, all fully connected feedforward, activated using Rectified Linear Units (ReLU) and trained with Adam optimizer. Each training run was conducted using a batch size of 32 for a minimum of 3500 iterations. Table I presents all simulation parameters.

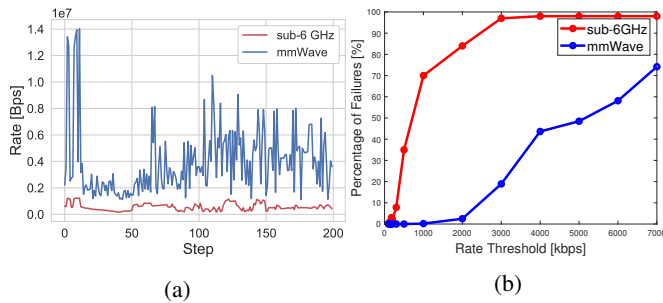
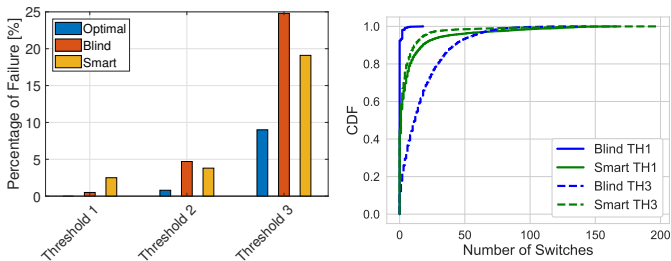


Fig. (1) Evolution of the UAV-UE rate at sub-6 GHz and mmWave along one single trajectory episode (a). Samples are collected at each step  $k$ , according to the framework described in Section II-D. In (b) we show the Radio Failures for a 3D trajectory at sub-6 GHz and mmWave



(a) Radio Failures for the Blind and Smart approaches, compared for the Blind and Smart Algorithm with an Optimal policy (b) CDF of number of switches for the Blind and Smart Algorithm with thresholds 1 and 3

Fig. (2) Performance of the band switch algorithms

### A. Simulation Environment

In Fig. 1a, we show the rate trend along with the same trajectory episode at sub-6 GHz and mmWave. The rate has sudden drops both at sub6GHz and mmWave, due to the presence of fading and obstacles. In particular, at mmWave, the rate can be very high or very low, due to the higher bandwidth and, at the same time, high sensitivity to blockages. In Fig. 1b we show the total percentage of detachments completing the UAV missions at one frequency only, sub-6 GHz or mmWave band, and without any band switch mechanism. Intuitively, the number of failures increases as we increase the rate threshold. Both the above results motivate the band switching approach presented in this paper.

### B. Band Switch Policies

The UAV-UE starts its trajectory at sub-6 GHz and can switch to the 28 GHz band. We consider a low threshold of 150Kbps at sub-6 GHz and 3Mbps at mmWave (Threshold 1), a threshold of 300Kbps at sub-6 GHz and 3Mbps at mmWave (Threshold 2) and a high Threshold 3 of 400Kbps at sub-6 GHz and 4Mbps at mmWave. In Fig. 2a we compare the blind, the smart and optimal switch algorithms for increasing thresholds in term of average percentage of radio failures. We observe that at low thresholds, the smart approach performs similarly to the blind approach. By increasing the threshold, and as consequence, the probability of a radio failure, we observe a

higher increase in the number of radio failures for the blind approach. While the blind approach switches the band anytime a radio failure occurs, the smart one offers the agent a generic framework that, interacting with the environment, learns to minimize the number of radio failures switching the band only when the target frequency provides higher throughput. As confirmation of this, in Fig. 2b we plot the Cumulative Distribution Function (CDF) of the number of band switches of the blind and smart approach for Threshold 1 and 3. We observe that in a high throughput regime, the smart approach outperforms the blind approach and can significantly reduce the number of switches.

## V. CONCLUSION

In this paper, we propose a DQN based approach to solve a communication aware trajectory problem for cellular UAV. In order to minimize the number of radio failures while reaching its target destination, we consider the UAV to exploit band switch policies without prior knowledge of the environment. We define and compare two joint trajectory and band switch DQN algorithms, that differentiate based on how the agent decide to switch the transmitting frequency. We show that a smart switch approach, where the band switch indicator is included as input state of the DNN, is able to outperform a blind approach in a high threshold regime.

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