# Reinforcement Learning Based Dynamic Power Control for UAV Mobility Management

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Abstract-Modern communication systems need to fulfill multiple and often conflicting objectives at the same time. In particular, new applications require high reliability while operating at low transmit powers. Moreover, reliability constraints may vary over time depending on the current state of the system. One solution to address this problem is to use joint transmissions from a number of base stations (BSs) to meet the reliability requirements. However, this approach is inefficient when considering the overall total transmit power. In this work, we propose a reinforcement learning-based power allocation scheme for an unmanned aerial vehicle (UAV) communication system with varying communication reliability requirements. In particular, the proposed scheme aims to minimize the total transmit power of all BSs while achieving an outage probability that is less than a tolerated threshold. This threshold varies over time, e.g., when the UAV enters a critical zone with high-reliability requirements. Our results show that the proposed learning scheme uses dynamic power allocation to meet varying reliability requirements, thus effectively conserving energy.

*Index Terms*—Reinforcement learning, Power allocation, Ultrareliable communications, UAV communications.

#### I. INTRODUCTION

Modern communication systems need to fulfill different, and often conflicting, objectives at the same time. The transmission power should be as low as possible while still meeting the high reliability constraints of modern applications. Furthermore, the reliability constraints vary over time and depend on the state of the system. For instance, for safety, the communication between a central controller and an unmanned aerial vehicle (UAV) requires high reliability when the UAV is close to other UAVs or close to an airport, and a self-driving vehicle requires higher reliability when the vehicle is close to an intersection. Varying reliability requirements may also be based on the switching of services over time where each service has a different reliability requirement [1].

For addressing the challenge of meeting demanding reliability requirements, collaboration of multiple distributed base stations (BSs) to serve users within the network's coverage area emerges as an effective strategy [2], [3]. However, using the same transmit power at all the cooperating BSs to achieve high reliability might not always be necessary. Also, in the context

of UAV communication, UAVs at an altitude will experience different channel gains which not only depend on the distances but also on the line-of-sight (LoS) and non-line-of-sight (NLoS) channel conditions [4], [5]. Therefore, to satisfy the reliability demands and use minimal transmit power, it is necessary to opportunistically leverage the LoS/NLoS channel conditions between the UAV and the BSs.

Creating an optimal power allocation scheme that adapts to the evolving environment and requirements due to user movement presents a significant design challenge. While employing advanced optimization techniques has the potential to yield a globally optimal solution, the practical feasibility of such approaches is often hindered by their high complexity [6]. Machine learning (ML), particularly reinforcement learning (RL), offers an attractive solution for such dynamic problems. By learning from the changing environment, RL can harness unique characteristics of UAV communication networks, enabling the agent to strategically utilize movement patterns and LoS/NLoS channel conditions between the UAV and the BSs.

In this work, we consider a UAV communication system in which the reliability requirement of the communication depends on the location of the UAV. We consider multiple cooperating BSs which serve multiple aerial users simultaneously. For this system, we employ an RL approach to minimize the overall power consumption while keeping the outage probability below a specified target. In particular, we propose a BS selection and power allocation scheme based on RL for a UAV communication system with varying reliability constraints. Our approach contributes to the understanding and optimization of jointly served UAVs, offering insights into enhancing network efficiency while providing high reliability demands.

While some previous works use RL for power allocation in UAV systems, they do not consider varying reliability requirements with energy efficient BS selection. In [3], the authors solve the cell association and power allocation scheme for minimizing the inter-cell interference caused by UAV communications. However, they do not consider the mobility of the UAVs and its affect on solving the optimization problem. While the considered scenario is dynamic, the service requirements do not change over time or depending on the location. In [7], RL is used to jointly optimize the UAV trajectory and mission completion time, emphasizing the importance of maintaining reliable communication connectivity with the ground cellular network throughout the UAV flight. In [8], the authors use

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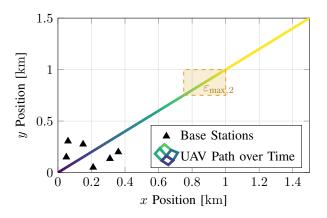


Figure 1. The considered communication scenario with fixed base stations and moving UAVs. Within the highlighted zone in the center, the reliability requirement is  $\varepsilon_{\max,2}$ , otherwise it is  $\varepsilon_{\max,1} > \varepsilon_{\max,2}$ .

RL for obtaining the optimal transmission power and cell association in addition to the optimal path of the UAV. They consider the tradeoff between the energy efficiency (EE) and wireless latency and uplink interference.

# **II. SYSTEM MODEL AND PROBLEM FORMULATION**

Throughout this work, we consider the following UAV downlink communication scenario, which is depicted in Figure 1. In a given area, K cooperating BSs are deployed at fixed locations. A total of N UAVs are moving inside of the area at the same time, and they are being served by the BSs on orthogonal resource blocks. We assume that the network has the location information of the UAVs moving in the service area. Therefore, the total receive power  $P_i$  at user i at time tis given as

$$P_i(t) = \sum_{k=1}^{K} |h_{ik}(t)|^2 P_{T,ik}(t), \quad i = 1, \dots, N, \qquad (1)$$

where  $P_{T,ik}$  denotes the transmit power of BS k to user i, and  $|h_{ik}|^2$  is the power attenuation between BS k and user i, i.e., the combined path loss and fading effects. These effects are modeled according to [9]. Each BS has a maximum transmit power of  $P_{T,max}$ .

While we assume that the positions of the UAVs and the fading statistics are known [10], the exact channel state is assumed unknown. Hence, the system will be in outage with a non-zero probability when the received power at a user is below its sensitivity s, i.e., the outage probability for user i at time t is given as

$$\varepsilon_i(t) = \Pr\left(P_i(t) < s_i\right). \tag{2}$$

Throughout the following, we assume that the channels are independent and identically distributed (i.i.d.) complex Gaussian distributions, which yields that  $|h_{ik}|^2$  follows an exponential distribution. For a single time slot t, i.e., for a fixed power allocation and fixed positions of all users, we can rewrite the outage probability as the probability of a sum

of exponentially distributed random variables with different expected values,

$$\varepsilon_i(t) = \Pr\left(P_i(t) < s_i\right)$$
  
= 
$$\Pr\left(\sum_{k=1}^K |h_{ik}(t)|^2 P_{T,ik}(t) < s_i\right)$$
  
= 
$$\Pr\left(T_i < s_i\right)$$
  
= 
$$1 - \bar{F}_{T_i}(s_i).$$
 (3)

Based on the above model, the random variable  $T_i$  is given as the sum of exponentially distributed variables  $|h_{ik}|^2 P_{T,ik} \sim \text{Exp}(\alpha_{ik})$  with different expected values  $\alpha_{ik}$ . The expected values are given by the product of transmit power, antenna gain, and path loss. The survival function  $\overline{F}_{T_i}$  of  $T_i$  is given by [11]

$$\bar{F}_{T_i}(s) = \sum_{k=1}^{K} A_{ik} \cdot \exp\left(-\alpha_{ik} \cdot s\right),\tag{4}$$

$$A_{ik} = \prod_{\substack{j=1\\j\neq k}}^{K} \frac{\alpha_{ik}}{\alpha_{ij} + \alpha_{ik}}, \quad \text{for } k = 1, \dots, K.$$
 (5)

For this expression to hold, we need to assume that all  $\alpha_{ik}$  are distinct. However, since they are the product of transmit power, antenna gain, and path loss, this assumption will hold almost surely in practice.

Depending on the application, a certain outage probability  $\varepsilon_{\max}$  can be tolerated. However, this tolerated threshold may depend on various factors and vary over time. In this work, we consider the scenario where a certain area is a critical area with a higher reliability constraint. Whenever a user is within this area, the outage probability should be less than  $\varepsilon_{\max,2}$ , while it only needs to be less than  $\varepsilon_{\max,1} > \varepsilon_{\max,2}$  everywhere outside the critical area.

# A. Problem Formulation

In this communication scenario, the primary goal is to adjust the transmit powers from the group of BSs that are serving the mobile UAVs, such that the overall transmit power is minimized. At the same time, the system aims to minimize the outage probabilities experienced by the users, such that each user remains below a specified threshold that is acceptable for the application. These two objectives are in conflict with each other, since reducing the transmit power to increase EE will lead to an increase of the outage probability. Additionally, due to the movement of the users, the optimal power allocation varies over time. Based on this, the optimization problem for this work is finding the optimal power allocation for the following multiobjective programming problem

$$\min_{P_{T,ik}} \left( \sum_{i,k} P_{T,ik}, \sum_{i=1}^{N} \mathbb{1}(\varepsilon_i > \varepsilon_{\max}) \right)$$
(6)  
s.t.  $0 \le P_{T,ik} \le P_{\max}$ 

where the aim is to simultaneously minimize the total transmit power and the number of users with a too high outage probability. Each transmit power  $P_{T,ik}$  is limited by a maximum power  $P_{\text{max}}$ .

# III. REINFORCEMENT LEARNING APPROACH

In order to solve the power allocation problem described in (6), we propose the use of RL, since it is a powerful optimization tool for the time-varying environment of the considered communication scenario.

The action that the RL agent takes, corresponds to a matrix of all transmit powers  $\mathcal{A} \in \mathbb{R}^{N \times K}_+$  for all BS-user pairs. The observation space consists of the current locations of all UAVs and the LoS/NLoS conditions between each user and base station pair. Based on the action (power allocation) and observations (locations, LoS condition), the outage probabilities  $\varepsilon_i$ for all users can be calculated according to [9] and (3). For the reward function r, we employ the following function that takes both the total transmit power and the reliability requirements into account:

$$r = \left(1 - \frac{\sum_{i,k} P_{T,ik}}{K P_{T,\max}}\right) - \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}(\varepsilon_i > \varepsilon_{\max}).$$
(7)

The power reward is given by the fraction of the unused power out of the total available transmit power. From this, the reliability penalty is subtracted, which is given by the fraction of users which are in the outage.

For our dynamic problem characterized by a continuous action space and a fluctuating environment, we employed different RL algorithms, including deep deterministic policy gradient (DDPG). Through empirical analysis, we determined that soft actor-critic (SAC) provides the best solution to our problem. The adaptability of SAC to sudden changes in the environment aligns seamlessly with the challenges posed by our time-varying conditions. More precisely, our problem requires an advanced strategy for continuous decision-making that adapts to the evolving dynamics of the environment. In this context, the emphasis placed by SAC on effective exploration becomes imperative for obtaining the optimal solution to the problem.

SAC employs a deep neural network (DNN) policy to generate stochastic actions based on the current state. Notably, SAC introduces entropy regularization, striking a balance between exploration and exploitation and avoiding premature convergence to sub-optimal policies [12]. The algorithm aims to maximize the weighted sum of reward and entropy of the action distribution, aligning with the need for a flexible yet focused decision-making strategy in our dynamic problem. SAC utilizes a soft Q-value function, considering the policy's entropy, and leverages a value function ensemble to enhance stability and robustness. With off-policy learning and re-parameterization, SAC efficiently learns from experiences collected during interaction with the environment.

# **IV. NUMERICAL RESULTS**

In this section, we numerically evaluate the proposed RLbased optimization in two different scenarios. First, we consider only a single UAV moving on a deterministic path. Next, we also evaluate a more complex setting with multiple users moving according to a stochastic movement model. In both cases, we consider an example with a square area, in which K BSs are placed in the bottom-left corner, cf. Figure 1. The critical area is located in the center of the overall area. In this critical zone, the outage probability target is set to  $\varepsilon_{\max,2}$ , while it is  $\varepsilon_{\max,1} > \varepsilon_{\max,2}$  everywhere else.

The implementation of the proposed RL solution from Section III and the numerical simulations in this section are made publicly available in [13].

#### A. Comparison Schemes

We compare our RL results with the following two baseline algorithms.

1) Full Power: As a first comparison, we use the Full Power scheme. These results are obtained by setting the transmit power to the maximum power at all BSs at all times. This is expected to yield the lowest outage probabilities as the receive power will be maximized. However, this comes at the cost of not saving any transmit power.

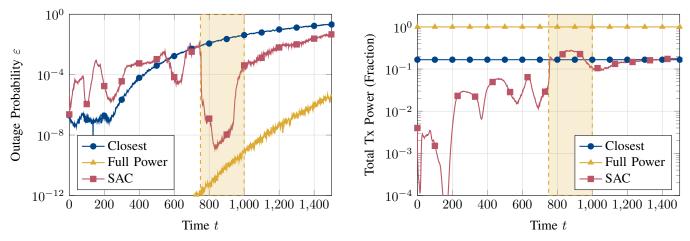
2) Closest Base Station: In the second strategy that we use for comparison, only the BS, which is the closest to a user is using the maximum power while all other BSs do not transmit to that user. In the following, we will refer to this scheme as Closest. With this baseline, we will get a much lower, yet constant, power consumption compared to the Full Power scheme. Specifically, since only one BS is active at full power, this strategy will use a constant power of 1/K of the maximally available transmit power for each user. However, this reduced power will increase the outage probability of the UAV compared to using the full power at all BSs.

# B. Single User – Deterministic Path

In the first numerical example, we assume that there is only a single UAV within the area. It moves in a straight line at a constant speed diagonally across the area as depicted in Figure 1. The area has a total size of  $1.5 \text{ km} \times 1.5 \text{ km}$  with the critical area being located between [0.75, 1] km in both x- and y-direction. In the critical area, the outage probability target is set to  $\varepsilon_{\max,2} = 10^{-7}$ , while it is  $\varepsilon_{\max,1} = 10^{-2}$  everywhere else. The user is served by K = 6 BSs.

The numerical results for this example can be found in Figure 2. First, we show the outage probability of the user over time in Figure 2(a). Since the UAV moves in a straight line at a constant speed, the time directly translates to the position within the area. Between time slots t = 750 and t = 1000, the UAV is inside the critical zone with the higher reliability target.

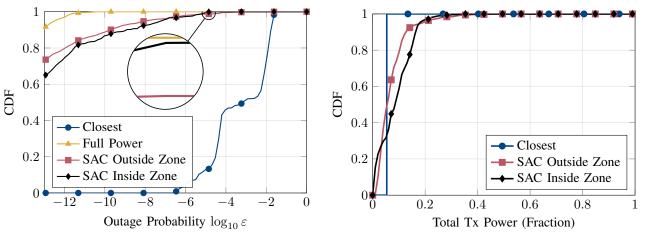
As expected, the outage probability is very low for the Full Power baseline. In particular, it is way lower than the target outage probabilities  $\varepsilon_{\max,i}$  in both the normal and critical zone. This indicates that transmit power could be saved without violating the outage requirements. For the Closest strategy, the outage probability is very low initially as the UAV starts close to the BSs. However, as it moves further away over time, the outage probability increases while using the same total



(a) Outage probability of the UAV over time.

(b) Total transmit power as a fraction of the maximum total transmit power.

Figure 2. Numerical results of the outage probability  $\varepsilon$  and the fraction of the total available power used to transmit over time. The single aerial user moves in a straight path diagonally across the  $1.5 \text{ km} \times 1.5 \text{ km}$  area, in which K = 6 BSs are placed. During the highlighted interval  $t \in [750, 1000]$ , the UAV is within the critical zone with a stricter reliability target. (Section IV-B)



(a) Distribution of the outage probability.

(b) Distribution of the fraction of used transmit power for a single user.

Figure 3. Numerical results of the distributions of outage probability  $\varepsilon$  and the fraction of the total available power. There are N = 3 aerial users that move in an area of size  $3 \text{ km} \times 3 \text{ km}$  according to the stochastic UAV movement model from [14]. A total of K = 19 BSs is placed in the area to serve them. At [0.75, 2] km in both x- and y-coordinates, there is the critical zone with a higher reliability target. (Section IV-C)

power, which is 1/K = 16.7% of the total available transmit power. In contrast to this, the RL approach with SAC achieves a lower outage probability while simultaneously using less or about the same power as the Closest baseline. Additionally, it can be seen from Figure 2(a) that the RL algorithm learns about the stricter reliability constraint within the high-reliability zone. It is able to adapt the power accordingly to meet the requirement, while it reduces the power again after the UAV leaves the critical zone. This can be clearly seen by the drop in the outage probability in Figure 2(a) and increase of power in Figure 2(b) between t = 750 and t = 1000.

# C. Multiple Users – Random Movement

After showing that the proposed RL-based solution performs well in a simple single user scenario, we next consider a more realistic scenario with multiple UAVs. In particular, we have N = 3 aerial users in an area of size  $3 \text{ km} \times 3 \text{ km}$ , in which K = 19 BSs are placed randomly at a height of 25 m. The critical area is located between [0.75, 2] km in both x- and y-direction. In this area, the outage probability target is set to  $\varepsilon_{\max,2} = 10^{-5}$ , while it is  $\varepsilon_{\max,1} = 10^{-2}$  everywhere else. Instead of following a deterministic path, the UAVs now move according to the stochastic movement model from [14].

The numerical results for this scenario are shown in Figure 3. Since we now have multiple users with a random movement, we show both the outage probabilities and the transmit power in terms of their statistical distribution. In particular, Figure 3(a) shows the cumulative distribution function (CDF) of the outage probability  $\varepsilon$ . First, it can be noted that the outage probability for the Full Power scheme is also very small, i.e., the CDF

reaches 1 at very small  $\varepsilon$ . This is expected and consistent with the single user results from Figure 2(a) in Section IV-B. Second, it can be seen that the outage probability almost never goes below  $10^{-7}$  for the Closest baseline. Additionally, around half of the time, the outage probability to the users is above  $10^{-3}$ . In contrast, our proposed solution using the SAC algorithm achieves a better outage performance, which is also taking the varying reliability requirements into account. Inside of the critical zone, almost all realizations are below the target threshold  $\varepsilon_{max,2} = 10^{-5}$ . Similarly, the same holds for the area outside the critical zone and its target threshold  $\varepsilon_{max,1} = 10^{-2}$ .

The distribution of the used transmit power averaged over all users can be found in Figure 3(b). Since the Full Power baseline always uses full power, we do not show it in the figure. The Closest scheme again uses a constant power of 1/K for each UAV, which results in the step function from 0 to 1 at  $1/K = 1/19 \approx 0.053$  in Figure 3(b), i.e., it constantly uses around 5.3% of the totally available power. For the RLbased solution, the transmit power varies between almost no output power and around 40% of the maximum. On average, the system uses 7.0% when the user is outside the critical zone and 8.6% when within. The higher transmit power for the critical zone is necessary to achieve the stricter reliability requirement  $\varepsilon_{max,2}$ . While the power consumption of the RL scheme is slightly above the Closest baseline, it achieves a significantly better reliability, cf. Figure 3(a).

# V. CONCLUSION

Energy efficient power allocation within the realm of multi-connectivity, where reliability requirements vary over time, demands complex real-time decision making processes. Traditional optimization tools do not adequately and efficiently address this complexity. In contrast, the application of machine learning, notably RL, is a well suited solution for such a dynamic problem.

In this work, we have implemented a model-free RL algorithm to optimize the power allocation in a UAV communication system under changing reliability demands. Our primary goal is to minimize the total transmit power of all BSs within the coverage area, while ensuring that outage probabilities stay below predefined thresholds. These thresholds change with position, such as when a UAV enters a critical zone with heightened reliability requirements. Numerical simulations show the effectiveness of our proposed solution for both single user and multi-user scenarios with stochastic movements.

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