A Simulation of a Telecommunications Channel with UAV-Based Q-Learning Network

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Abstract

In this paper , we present a simulator that replicates a communication channel between terrestrial users using low-altitude airborne mobile stations (Unmanned Aerial Vehicles). Through a Q-Learning network, the UAVs determine the optimal position to occupy to improve transmission between users and converge towards these optimal states. This system lends itself to various applications, including the restoration of the telephone network in areas without coverage or affected by natural disasters, and the establishment of mobile radio bridges to connect remotely controlled vehicles in conflict scenarios, making communications difficult to intercept. The results presented were obtained by tailoring the model in different scenarios, according to a realistic concentration and distribution of buildings in the four analyzed environments

Keywords

Q-Learning, UAV communications, telecommunications

1. Introduction

Recent developments in international conflicts have shown how the use of drones has influenced the course of the most significant war scenarios. Even in this context, machine learning is finding increasing applications, enhancing the capabilities and precision of drone operations [1, 2, 3, 4, 5, 6, 7].

This article proposes an application of UAVs in the field of communications. In particular, a model for radio communication between users through mobile stations has been developed.

In accordance with recent studies, future communicatio networks are anticipated to integrate non-terrestrial networks, including Low Earth Orbit (LEO) satellites and High Altitude Platform Systems (HAPS) utilizing Unmanned Aerial Vehicles (UAVs) [8, 9, 10, 11, 12]

Among the studies present in the literature, various systems for managing the movement of UAVs have been experimented with: centralized and distributed systems. The centralized system consists of a terrestrial radio station for estimating channel parameters and controlling the telemetry signals of the UAVs [13, 14] while the distributed system is characterized by independent drones that autonomously estimate the channel parameters [15, 16]. This study focuses on the modeling and simulation of a centralized system. To achieve maximum telephone coverage, the system implements a Q-Learning network for selecting the optimal position of the drones. The effectiveness of using air-to-ground telecommunications systems with UAV-type transmitting stations is estimated by extracting some characteristic parameters of wireless communication, including (i) connection throughput and (ii) number of failed connections.

It is worth noting that there are already studies focusing on modeling a telecommunications system with low-altitude mobile repeaters. These systems aim to find the optimal altitude of the aircraft given a fixed transmission power [4], optimize the ratio between power efficiency and throughput [17], or estimate the maximum ground coverage area [4, 18].

2. Materials and methods

2.1. Parameters and their description

The descriptive parameters of the simulated model are divided into the following three macro groups:

1. *Channel statistical characteristics*
   It consists of a set of parameters that describe the statistical characteristics of the environment in which the system operates, including:
   Environment: It is composed of four categories (Rural, Suburban, Dense Urban, and Highrise Urban) that differ in the concentration, density, and height distribution of buildings. The determination of the environment establishes the Gaussian distribution parameters of Excessive Path Loss, a parameter for estimating additional losses [4, 19, 20, 21, 22, 23].
2. *Connection parameters*
   That is, the specific characteristics of the channel:
   Transmission powers: are the power levels of the repeaters and the transmission devices of the users.
   Transmission band: including the parameters of occupied bandwidth and carrier frequency.

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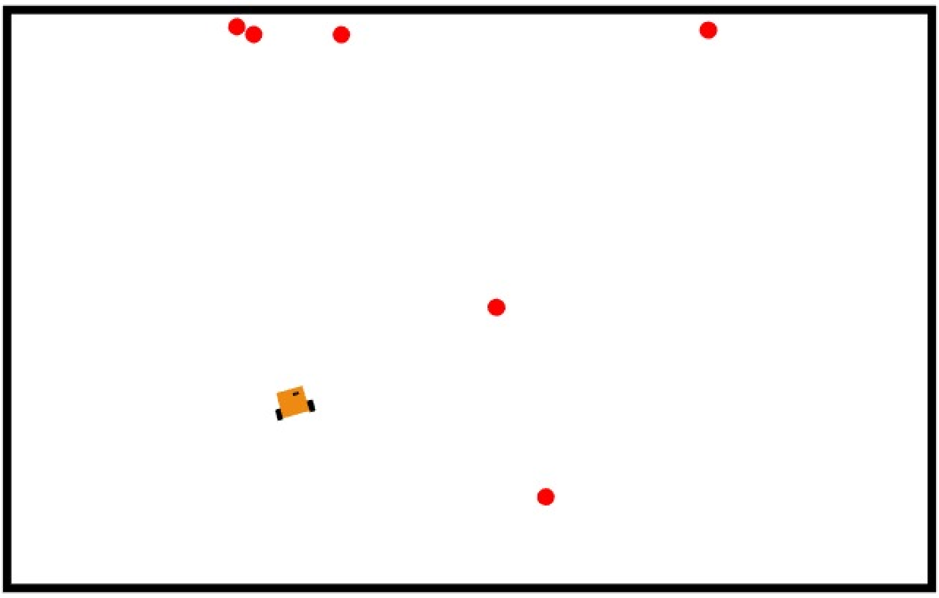

Figure 1: Graphic interface where red points represent users and robots represent UAVs.

Modulation: The system, modulated in OFDM, allows for the selection of the number of subcarriers and their respective modulation.
Minimum rate: is the minimum throughput below which the connection fails.

3. *Properties of the UAVs and users*
   That is, those typical quantities of the movement of users and drones, including:
   Velocity: This refers to the speed of the users and the UAVs.
   Number of users served and mobile repeaters: indicate the number of mobile radio stations and users present in the simulation.
   Simulation area: indicates the simulation area considered, approximated with the base and height of the equivalent rectangle.

2.2. Robotarium

Robotarium developed by the Georgia Institute of Technology in collaboration with Heriot-Watt University in Edinburgh allows for the simulation of the behavior of robots and drones in a predefined area. It is possible to display the movement of users and drones in the environment as needed [24].

2.3. Calculation of Throughput and Failed Messages:

The algorithm for calculating throughput (T) and failed connections consists of two phases:
Initialization phase

- User and UAV positions are randomized;
- The system precomputes the maximum channel capacity (C), given the input parameters as Band(B), Subcarriers(S) and Modulation (M) [25]:

$$C_{max} = 2 * B * log_2(S * M) \tag{1}$$

Estimation phase

1. The system creates a list of connections, so that each user is assigned one with which to establish the connection;
2. The system, starting from the first connection, calculates all sender-drone and drone-receiver throughputs (2∗number of drones), assigning to each drone the worst of the two values, using the equation:

$$T = B * log_2(1 + \frac{Power}{P_{noise} * Loss}) \tag{2}$$

3. Since the system is centralized, for each pair of users, the best UAV to establish the connection is chosen, and only that throughput value is considered;

4. Based on the throughput value:
   - if the value is equal to or greater than the maximum channel capacity (1), this is assigned as the result for the connection;
   - if the value is below the established threshold, the counter for failed messages is incremented;
   - for any other value, the connection is successful, and the calculated throughput value is assigned to the connection;
5. The simulator stores the data and starts the iteration counter, assigning each UAV a new position based on the Q-learning algorithm. 2.4;
6. At each iteration, the system checks if the drones have reached their final positions, then returns to the point 1.

2.4. Q-learning

Q-learning is a reinforcement learning algorithm that helps an agent learn the best actions to take in various states to maximize rewards. The Q-Learning algorithm [26] involves associating each drone with a two-dimensional matrix where rows indicate states and columns indicate actions. The system states correspond to the central position of the cells into which the drone's operating area is divided. The actions represent the behaviors that a UAV can adopt in a given state. In the context of this article, the environment is divided into 40 states (cells of $400m * 400m$) while the actions available to the aircraft are 5: one for each cardinal direction and a fifth action corresponding to no movement. It should be noted that the aircraft can move a maximum of one cell per cycle.

The reward function, a parameter for updating the Q-Table, is as follows:

$$Reward = 100 * Rate - Failed\,Messages \tag{3}$$

3. Experimental results

The experimental results, obtained to demonstrate the correct functioning of the presented simulator, were achieved using the following parameters:

The data is presented as the average of throughput values and failed connections over an entire training epoch. Below, we can see a training conducted over one hundred epochs in the four environments 1 using a single drone:

It's noticeable that the main issue is the number of connections, which is due to the area to cover. Performing training over fifty epochs with three UAVs yields:

Table 1
Connection parameters

Parameters	Values
Band	20 Mhz
Carrier frequency	2 Ghz
UAV transmission power	1 W
User transmission power	0.3 W
Minimum allowable rate	256 kbps
Number of subcarriers	1200
Subcarrier modulation	QPSK

Table 2
UAV and User parameters

Parameters	Values
UAV speed	40 km/h
User speed	6 km/h
Number of users	6
UAV number	1-3
Simulation area	3.2 Km x 2 Km

Table 3
Training parameters

Parameters	Values
Epochs	40 km/h
Iterations by period	6 km/h
Alpha	6
UAV number	1-3
Gamma	0.8

Table 4
Average over the last 20 epochs of results

Environment	Throughput	Connections failed
Rural	15,6 Mbps	2.95/6
Suburban	7,0 Mbps	3.96/6
Dense Urban	4,79 Mbps	4.87/6
Highrise Urban	0,58 Mbps	5.86/6

4. Conclusion

In this article, a simulator of a communications system has been presented, capable of providing metrics on the quality of the air-to-ground wireless network consisting of airborne repeaters in different environmental contexts. Furthermore, the operation of the simulator has been tested in four environments, evaluating its effectiveness with one or more UAVs. Through simulation obtained with real parameters, data reflecting the actual operating conditions of such a system in various scenarios have been derived. Further developments of the simulator include the possibility of modeling the statistical channel parameters directly from the distribution, density, and height of buildings. Additionally, a relaying system between drones can be implemented to expand the system's

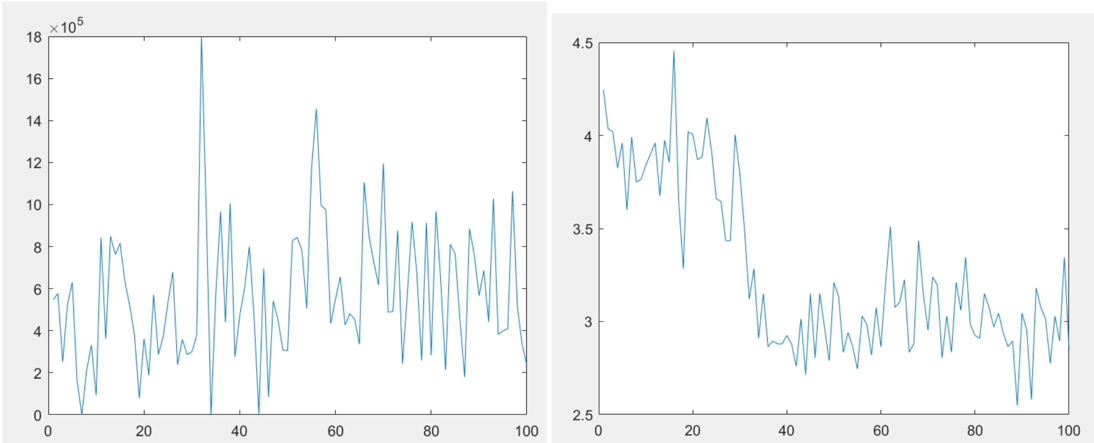

Figure 2: simulation in a rural environment, on the left throughput x epochs, failed messages on the right x epochs

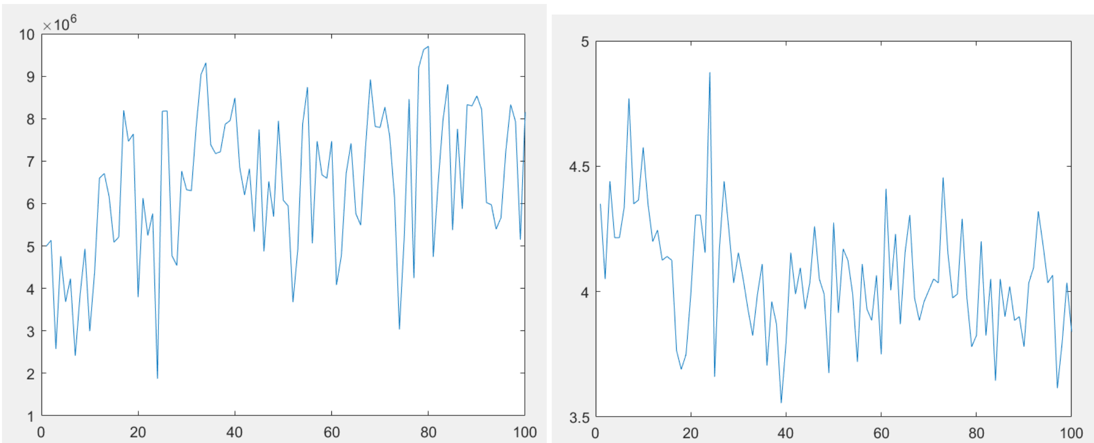

Figure 3: simulation in a suburban environment, on the left throughput x epochs, failed messages on the right x epochs

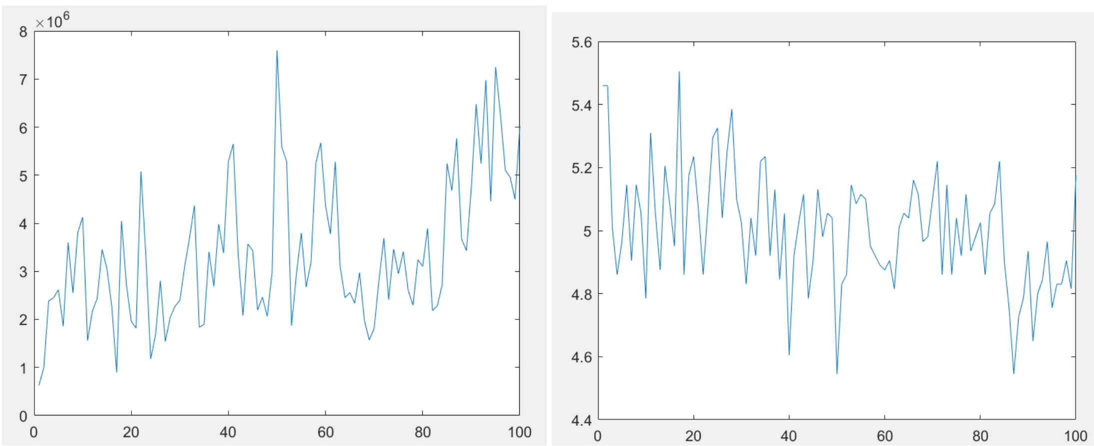

Figure 4: simulation in Dense Urban environment, on the left throughput x epochs, failed messages on the right x epochs

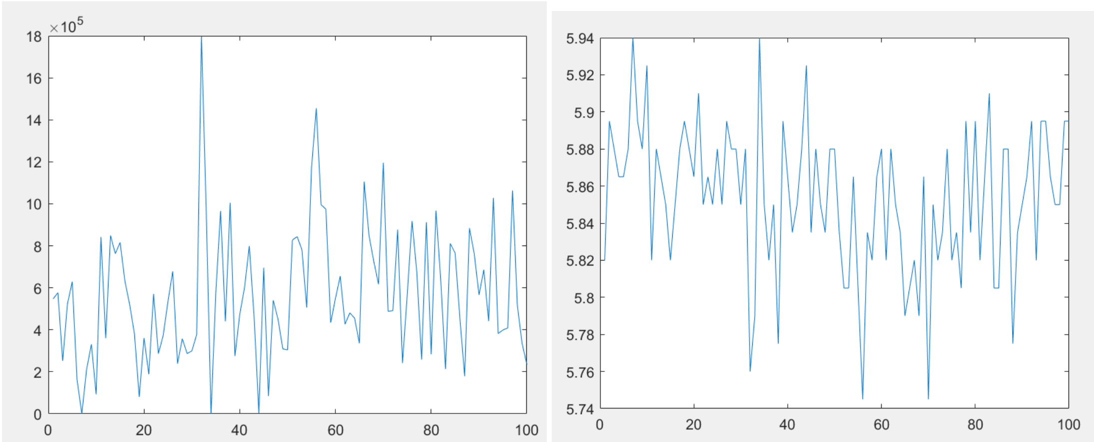

Figure 5: simulation in a highrise urban environment, on the left throughput x epochs, failed messages on the right x epochs

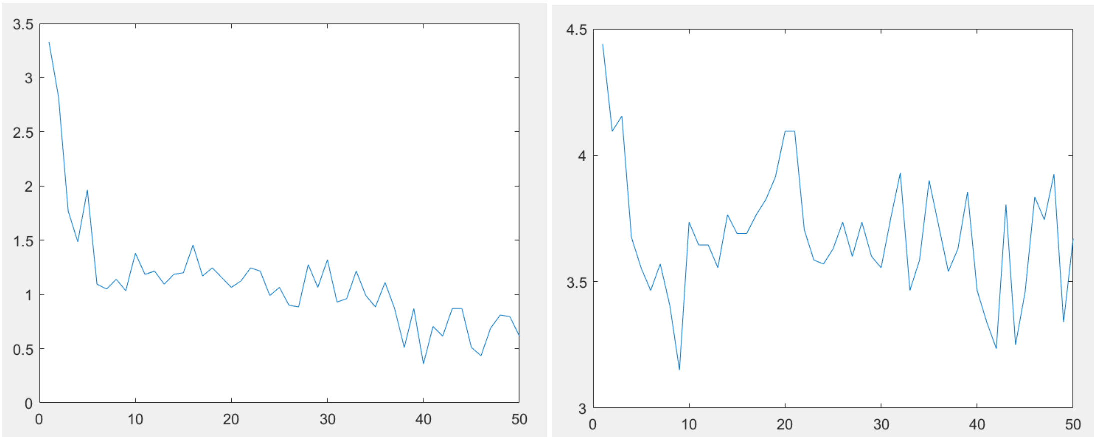

Figure 6: failed messages on the left x epochs in rural environment, failed messages on the right x epochs in suburban environment

Table 5
Average of failed messages in the last twenty epochs for the single UAV compared to the average in the last ten epochs for three UAVs

Environment	1 UAV	3 UAV
Rural	2.95	0.78
Suburban	3.96	3.51

coverage.

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