Analysis and prediction of path loss in UAVBS air-to-ground communication using neural networks

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Abstract. *Abstract. Unmanned aerial vehicles bases stations (UAVBS) have many applications in telecommunications. Enables integration into systems in order to provide network signals for users on the ground. The electromagnetic signal from the UAV is characterized by air-to-ground propagation. At different altitudes, the signal suffers losses along the way, thus facing several problems related to transmissions, such as attenuation, fading, and distortion. This paper studies UAV air-to-ground path loss at different altitudes of the UAV. To this, implement a field measurement campaign, which collects and analyzes the signal strength in wireless networks. Finally, it proposes the use of recurrent neural networks to predict the propagation loss in the network. The results were found to show good accuracy in the chosen scenario.*

1. Introduction

Unmanned Aerial Vehicles (UAVs) are being used in various telecommunications applications. UAVs are equipped with a wireless network and are considered temporary air base stations. In remote areas, the use of UAVs makes it possible to monitor sensors, thus allowing data collection. These temporary mobile networks bring advantages compared to fixed ones since they can be moved to different areas according to the need.

UAVs have become an essential component in many wireless communication systems due to their rapid deployment, mobility, and flexibility. Due to its dynamics of providing access to networks at different altitudes, the UAVs' electromagnetic signal suffers losses along the way, thus facing several problems related to transmissions, such as attenuation, fading, and distortion.

Deploying UAV communications is challenging due to the obstacles that contribute to high uncertainty path loss. The wireless signal is characterized by air-to-ground propagation and features a Line of Sight (LOS) and No Line of Sight (NLOS) between the transmitter and receiver. Thus, the transmission quality is related to the altitude and frequency of the drone [6]. The figure below demonstrates the signal coverage usage of UAVs at different altitudes.

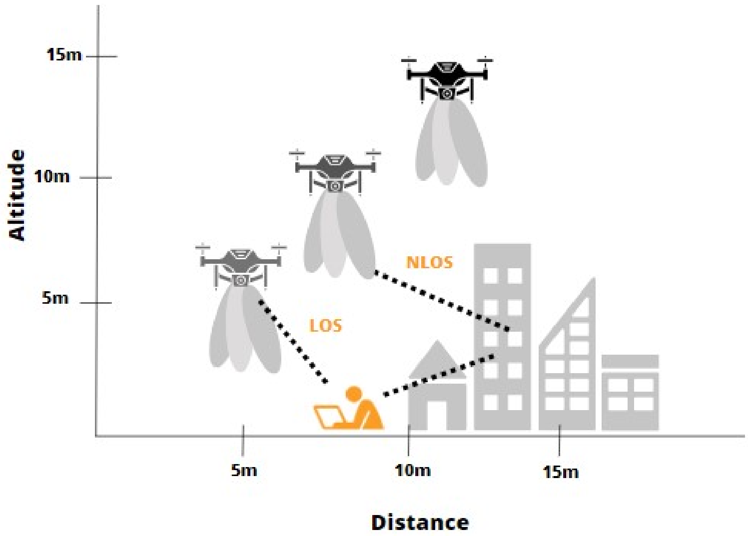

Figure 1. UAV BS in differences altitudes.

In order to analyze air-to-ground propagation losses with UAVs, this research was divided into two stages. The first carried out a campaign that collected and analyzed wireless signal level strength. And the second step proposes a neural model, which uses signal strength data treated as inputs, to predict the network propagation loss. The model produced is then compared with a traditional empirical model, achieving better results.

The sections of this article are organized as follows: Section 2 contains related work. Materials and methods are in section 3. Section 4 presents the results. Finally, in section 5 are the final considerations.

2. Related work

In the literature, there are several works related to the improvement of electromagnetic propagation in wireless networks, which are based on mathematical and computational modeling.

For mathematical modeling, there is the work of [2] in which drones serve numerous users in an accessible region based. Another model is an empirical model used to calculate propagation loss in mobile systems and contains correction factors for urban, suburban, and rural areas [3]. Computational models are also used to predict propagation losses. Due to the uncertainty of the propagation channel in the rural precision farming environment, the path loss prediction comparison was investigated by conventional optimization algorithms [6].

In paper [1], we consider the sum power minimization problem via jointly optimizing user association, power control, computation capacity allocation, and location planning in mobile edge computing. The numerical results show that the proposed algorithm achieves better performance than the conventional approaches.

The challenge of air-to-ground communication is to assess the propagation scenario in various environments, channel probing, link distance or path loss between transmitter and receiver, elevation angles, and antenna placement on the UAV [5]. The existing works are mainly based on empirical models, such as the free-space model and log-distance model, which depend on data collected in specific propagation scenarios [7].

This proposal differs from previous works, it proposes a solution using neural networks. Thus having one more contribution to studies that need to carry out a measurement campaign or deploy a real solution.

3. Proposed System Model

This section presents the methodology used and its 02 steps: measurement campaign and proposed neural network. To implement the experiments, it was necessary to create a test environment.

3.1. Measurement campaign

3.1.1. Area

The area chosen for the experiments is the university campus. With more than 300 students, it is possible to carry out a study so that UAVSBS can provide internet at specific events. The area is composed of building constructions and vegetation that causes several challenges to provide access to users.

3.1.2. Horizontal Position the UAV

Initially, the simulation found the ideal horizontal positioning of the UAV [15]. It assumes that there are 300 stationary users in the specified uniformly distributed 100x100 geographic area. Note that in the simulation choice was the center of user grouping. The simulation is performed in Matlab®2022 shown in the table below.

Table 1. Simulation parameters

Parameter	Description	Value
UAV flight	time	10 min
Tx	antenna gain (UAV)	5.1 dBi
Rx	antenna gain (tablet)	3 dBi
Carrier	frequency	2.400 – 2.480 GHz
Band	width	20 MHz
a	Elevation angle	55 degree

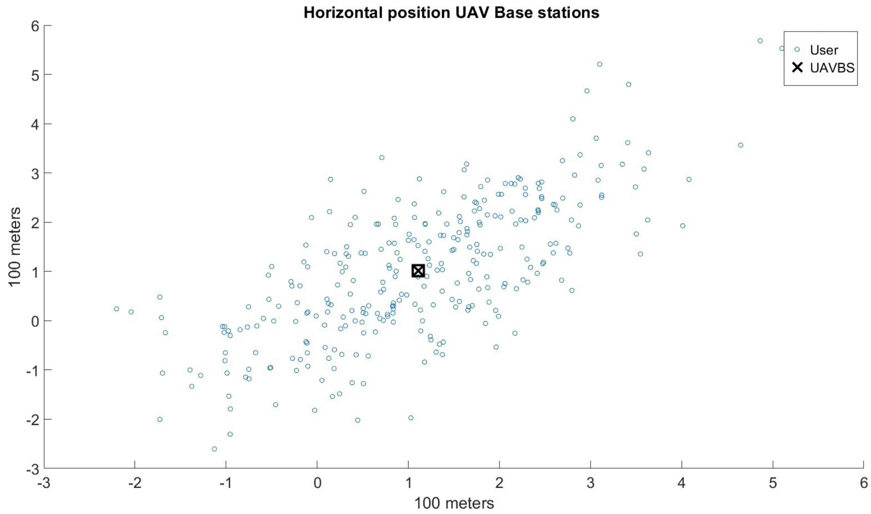

Figure 2. Horizontal position the UAV

After finding the horizontal placement of the UAV, the drone is positioned and points are chosen to measure the signal strength. With Los (points a and d) and without Nlos (points b and c), according to the signal attenuation, as below:

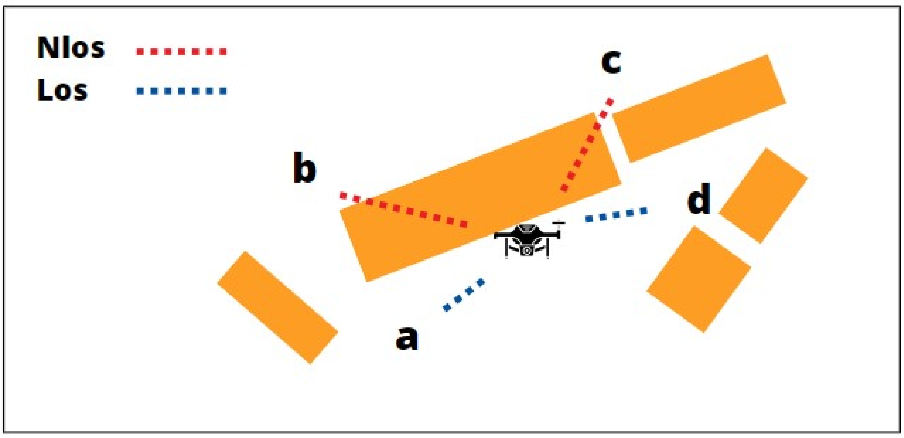

Figure 3. Chosen area

3.1.3. Ideal altitude the UAV

It is also necessary to find the ideal altitude for the UAVBS in order to provide better coverage and QoS for users [15]. Measurements were performed at different altitudes: 10 mts, 20 mts and 30 mts.

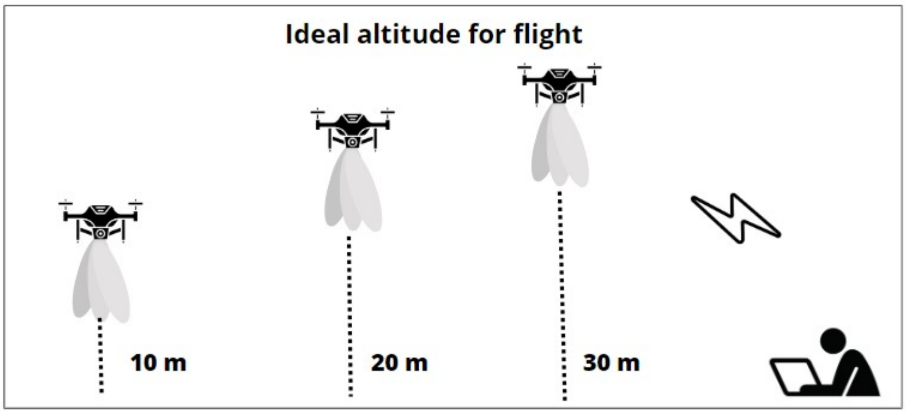

Figure 4. UAV BS providing signal wireless at different altitudes

After measuring at each point (a, b, c, d) for each drone height (5m,10m, and 15m), the collected total data were 2998 samples.

3.1.4. Used equipment

In the real environment, one of the following equipment was used. O software Signal Network Pro application was used, which collects the signal level of the device connected to the network in real-time. Measurements were performed with a Samsung Tab 6 tablet and a Tello UAV with a built-in router. The UAV and the Tablet ground are connected by using WiFi portable and links IEEE 802.11n [14].

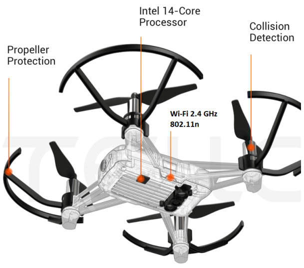

Figure 5. Drone used.

3.1.5. Data

Signal level measurements were performed between the mobile device and the UAV. The default configuration of the network uses the 802.11n protocol, with a frequency of 2,5GHz.

The original data are saved in a LOG, which contains various information, distributed in different fields, being necessary to filter them, leaving only: the received signal level and GPS coordinates. The calculation was performed using the latitude and longitude GPS coordinates, in order to find the real distance from the user to the UAV [13], values were inserted in the formula below:

$$d = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{1}$$

3.1.6. propagation using the empirical GUT-R model

Unlike other empirical wireless network models, the GUT-R was designed to calculate propagation losses in flying base stations. These stations allow you to cover areas at different altitudes.

To investigated The path loss characteristics between Rx and Tx can be investigated using the empirical GUT-R model. The model depends on parameters such as e direct line-of-sight (LOS), antenna gain, GS height, ground reflected, UAV height, and horizontal separation distance [11].

$$\begin{aligned} P_L^{\mathrm{GUT-R}}(\mathrm{dB}) = & 40 \log d_c - (10 \log G_g + 10 \log G_u \\ & + 20 \log h_g + 20 \log h_{\mathrm{UAV}}) \end{aligned} \tag{2}$$

To calculate the path loss in the network in area free [12], the captured values were inserted in the formula below:

$$L = 10log(\frac{pT}{pR}) - g \tag{3}$$

Where L is the path loss; Pt is the transmitted power; Pr represents the power of the received signal and G is the sum of the transmission and reception gains.

3.2. Recurrent Neural Networks

This work used the recurrent network, Long Short-Term Memory (LSTM), to estimate future values of propagation losses during the UAV flight. In [5] uses recurrent neural networks to predict path loss distributions for different drone altitudes. Due to their characteristics, recurrent neural networks are used to make predictions in time series. In the [10] Applying a new framework for the prediction of received signal strength (RSS) in mobile communications based on artificial neural networks (ANNs).

3.2.1. Input data parameters used

As inputs to the neural network, we have the power of the received signal, in different altitudes, and for the output of the network, the calculation of predicted path loss [9].

With sliding time window setting, Adam optimizer is gradient-based method with an adaptive learning rate. The signal strength data from the UAVs were divided into 80 percent for training and the percent for testing [8]. 200 epochs were used for model training and neural model implementation was performed using Python. The network input parameters were: UAV Tx power, UAV height, user Rx, received Rx power, distance from the UAV/user.

3.2.2. Metrics used

To evaluate the developed neural model, the metric of mean squared error (MSE), R squared (R2) and root mean squared error (RMSE) were used. The performance of the proposed neural model was evaluated with metrics based on the work of [5] [6]

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{y}_i)^2 \tag{4}$$

$$R_a^2 = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n} sum_{i=1}^{n} (\hat{y}_i - x_i)^2} \tag{6}$$

4. Results

In this section, we discuss the experiments carried out in the field measurement campaign, and also, show the performance of the proposed model in the propagation loss of the UAV network.

4.1. Measurement campaign analysis

Initially, the collected signal intensity levels were statistically evaluated. The data have a normal distribution as shown in the tablet and figure below:

Table 2. Colleted data

dBm	dBm	Lat	Log
-101	-101	-1.269963523	-47.91106632
-101	-101	-1.269963523	-47.91106632
-101	-101	-1.269963523	-47.91106632
-102	-101	-1.269963523	-47.91106632
-102	-101	-1.269963523	-47.91106632
-103	-101	-1.269963523	-47.91106632
-103	-101	-1.269963523	-47.91106632
-100	-101	-1.269963523	-47.91106632

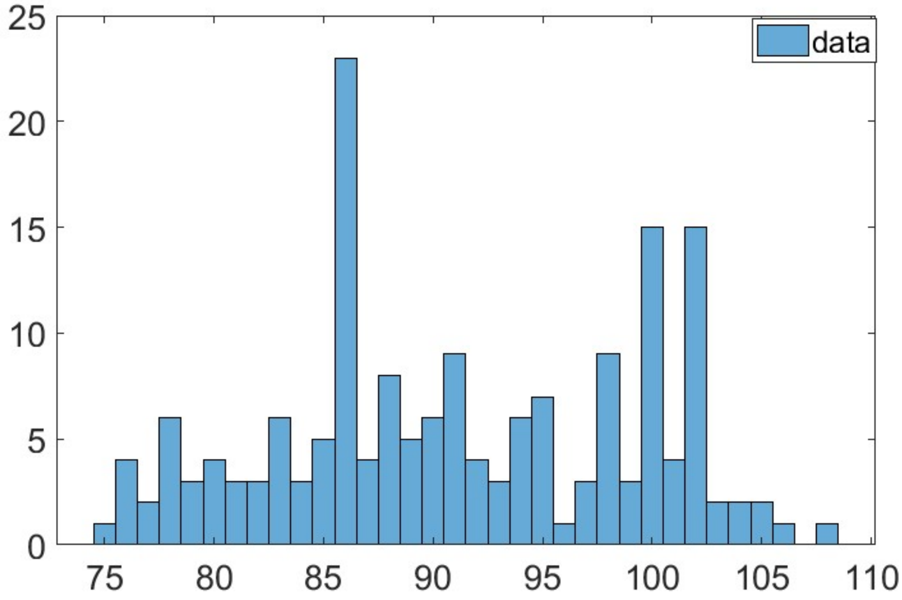

Figure 6. Data histogram

Then the captured data are plotted by observing the loss of propagation of the air-to-ground signal intensity along the path. signal fading occurs along the path from the van to the ground user.

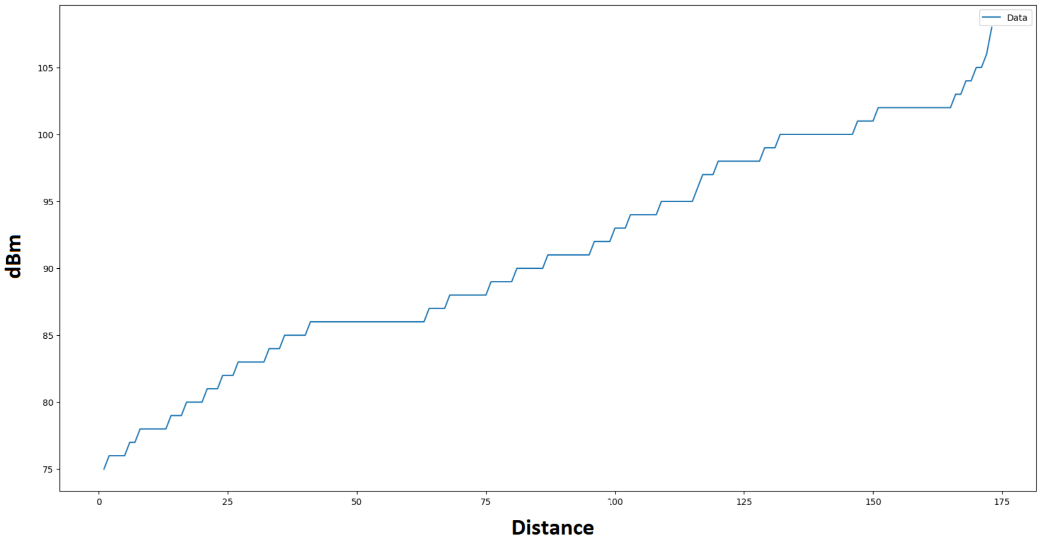

Figure 7. Signal power collected

Due to the altitudes of the UAV, path loss occurs differently. Values of 5m are best, followed by values of 10m and finally 15m of altitude. These parameters are used to choose the altitude at which the UAV will be deployed, as this directly affects the quality of service provided to the user on the ground. It can be seen in the tablet and figure below:

Table 3. average of altitude values

Altitude	Value
5m:	91,15 dbm
10m:	92,77 dbm
15m:	93,57 dbm

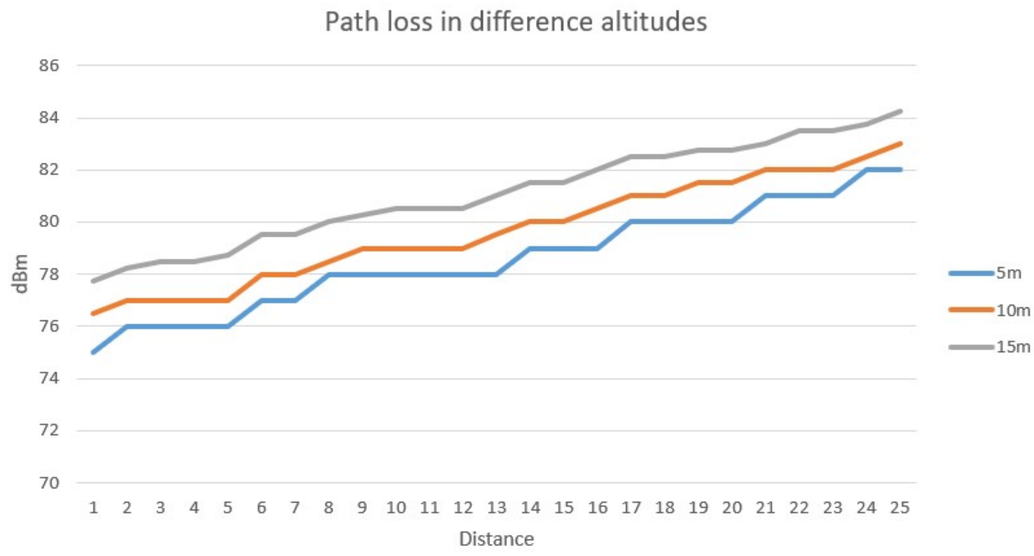

Figure 8. Signal power collected in the three altitudes

In this experiment with the available parameters and equipment, the choice of altitude would be 5m. However, if you have a larger area to cover, it would be interesting to opt for the 10 m altitude. This feature allows UAVs to be used to cover different scenarios, since when performing a new positioning both the coverage radius and the emitted power change, providing access to more users on the ground.

4.2. Forecasting using neural networks

After analyzing the collection data, the developed model was used to predict wireless network path loss.

The need to create a neural model to predict path loss is to have a representation closer to reality since traditional maths models tend to have less reliable results. Thus, this neural model created will aim at a more confident and close to the real scenario.

In addition to path losses, this neural model also involves distance, Tx altitude, Rx altitude, and elevation angle in the model parameters. A number of LOS and NLOS samples were collected, allowing to perform prediction using neural networks.

Then the neural network performed the prediction, and obtained MSE: 0.33, RMSE: 0.43 and R2: 0.89. ModelCheckpoint was used, which stops training when the loss of validation is no longer improving. This case stops in the 200 epochs, as can see in Table 3 and Figure 04.

Table 4. Results ANN.

Parameter	Value
MSE:	0,33
RMSE:	0,43
R:	0,89

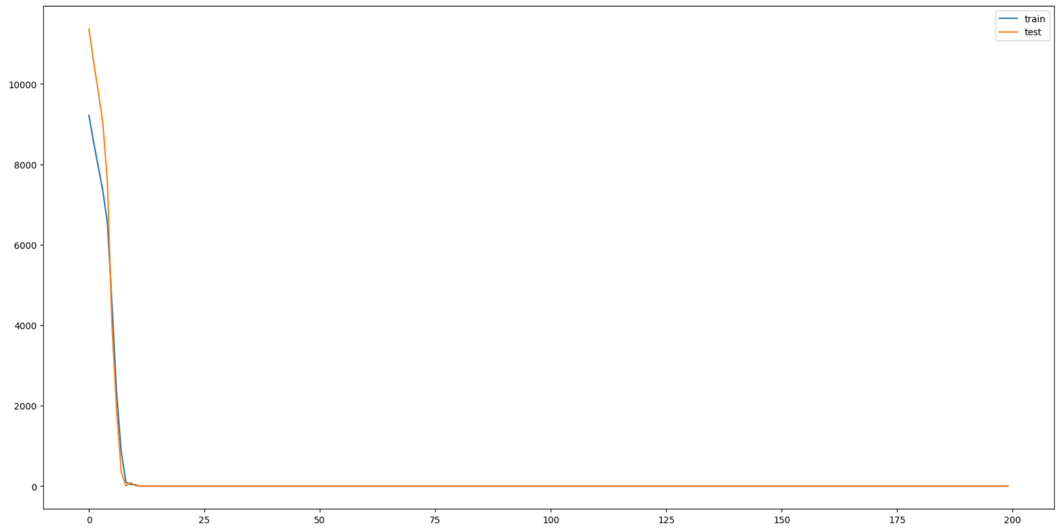

Figure 9. Epochs train ANN

The recurrent neural network was able to predict future values of air-to-ground path loss from the collected signal intensity levels. There are many parameters related to path loss and they serve as input features in our models. For example, the path loss values of UAVs at different Tx and Rx altitudes. In selected low-altitude UAV scenarios, path loss values are better than others and are used to forecast, as shown in the figures below:

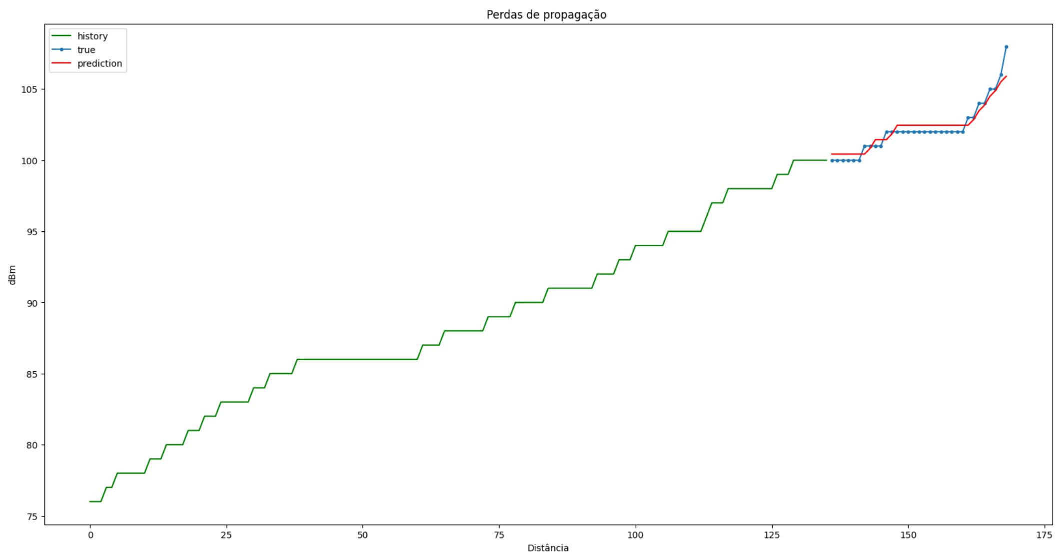

Figure 10. Forecast ANN in all data

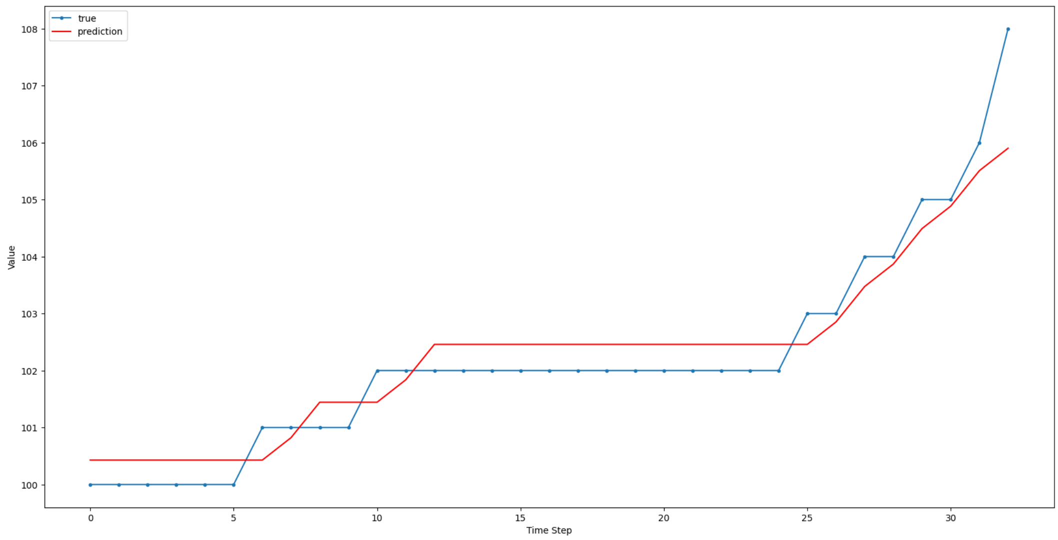

Figure 11. Forecast ANN

4.2.1. Comparison between neural model and GUT-R model

The GUT-R empirical model is used for propagation between UAV and ground users. The model considers the propagation channel, in which the received signal is the sum of line-of-sight (LOS), reflection to user line-of-sight (NLOS), and different drone altitudes.

The need to create a neural model to predict path loss that tends to be more realistic. Traditional mathematical models tend to have less reliable results. Thus, this created neural model proved to be more confident and approached the real scenario.

In our study, the data presented to the GUT-R empirical model, present worse results, since the empirical models tend to make only an approximation, shown in table and figure below:

Table 5. Comparison Neural x GUT-R model

	GUT-R	NEURAL
MSE:	16,19	3,5
RMSE:	15,56	4,23
R:	0,26	0,95

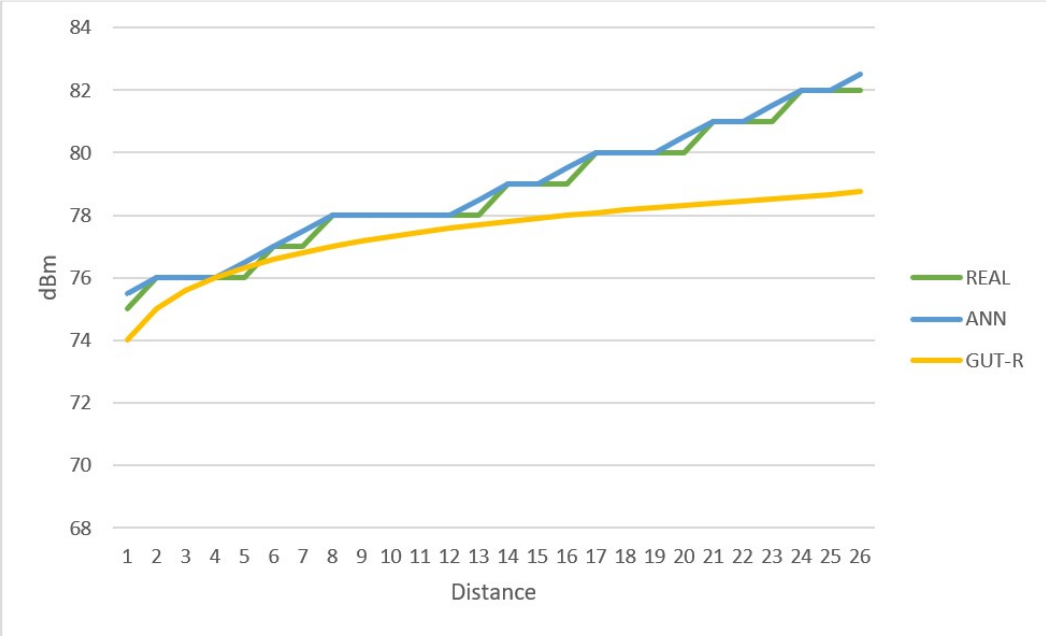

Figure 12. Epochs train ANN

Thus, the use of neural networks is more interesting than traditional GUT-R models. In this way, the present study contributes to research that focuses on measurement campaigns, since the results are closer to the real world.

5. Conclusion

The article presented a study on signal propagation in air-ground type using UAV. A campaign to measure signal intensity levels was carried out to estimate the ideal height and altitude ideal the VANT. Finally, we proposed a recurrent neural network model to predict propagation loss in wireless networks.

The measurement campaign was able to collect, analyze and evaluate the UAV's air-to-ground signal strength levels. For this, he described the implementation steps of a UAV to provide internet access on a university campus. A numerical simulation was performed to find the horizontal positioning of the UAV. It showed that different altitudes will get different levels of signal strength. It is necessary to evaluate the ideal height for the individual objective.

The neural network was proposed to perform network signal level prediction. The chosen network was the recurrent one and after being trained, it carried out the prediction, reaching the following values of MSE: 0.33, RMSE: 0.43, and R2: 0.89. The created neural model was compared with the GUT-R empirical model, achieving better results to predict network path loss, and contributing to a model closer to the real world.

The result proved to be more adequate to predict signal levels in the studied environment. For future work, it is proposed to analyze the space studied by increasing the number of UAVs.

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