Prediction of Communication Signal Strength with UAVs Using Artificial Neural Networks

Jaqueline dos Santos Silva, Evelio Martín García Fernández and Alessandro Zimmer

Abstract— **Recognizing the importance of unmanned aerial vehicles in urban traffic surveillance, this research proposes an artificial neural network to predict Wi-Fi signal strength during drone flights. The developed multilayer perceptron algorithm utilizes input features such as altitude, elevation angle, terrain type, distance to the controller, speed, and battery percentage. For validation, the neural network's outcomes were compared with the Longley-Rice model. The achieved RMSEs of 1.95 dB, 2.93 dB, and 2.39 dB for rural, suburban, and urban regions, respectively, highlight the multilayer perceptron as a promising solution for signal strength prediction in drone flights.**

Keywords— **uav, artificial neural networks, path loss prediction, signal strength, radio-mobile**

I. Introduction

Drones, categorized as Unmanned Aerial Vehicles (UAVs), have become noteworthy due to their versatile applications in various sectors such as agriculture and urban traffic management [1]. They can be used to enhance connectivity in isolated or disaster-impacted areas where conventional communication infrastructures are difficult to establish [2]. Ensuring reliable communication signals is crucial for drone operations, particularly in security operations such as real-time monitoring and collision avoidance [3]. Also, it is important to optimize energy efficiency and select appropriate modulation techniques and communication protocols to preserve communication integrity during drone flights [1].

Machine learning has emerged as a subfield of artificial intelligence, enabling new methods for problem-solving. In the context of drones, using machine learning techniques is a promising and mostly unexplored area, offering many opportunities for research and innovation. While traditional propagation models provide satisfactory solutions for signal strength prediction and network planning, applying machine learning techniques could yield more accurate results in situations where one of the communication nodes is in constant motion, due to their potential to process large volumes of data with precision [4]. For this purpose, a multilayer perceptron was developed to predict signal strength in drone flights. Additionally, the Longley-Rice propagation model, implemented through Radio Mobile software, was used for this purpose, allowing the accuracy of the machine learning algorithm to be compared with a conventional propagation model.

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II. Previous Works

The study conducted in [7] proposes the development of an agricultural monitoring system through the integration of drones, IoT, and LPWAN (Low-Power Wide-Area Network). The research addresses the effectiveness of LoRaWAN (Long Range Wide Area Network) technology in providing wireless coverage in drone flights, evaluating the most accurate path loss model for the scenario under analysis. The RSSI (Received Signal Strength Indicator) measurement results demonstrated coverage exceeding 10 km, indicating the effectiveness of LoRaWAN in applications involving drones.

The irregular terrain Longley-Rice model and the ECC-33 model were considered for calculating signal strength, and although initially, satisfactory results were not obtained with these models, refinements in the ITM model significantly improved the accuracy of the obtained RSSI results, demonstrating its suitability for coverage prediction in rural environments [7].

Additionally, the performance of LoRaWAN was tested at different flight speeds to quantify the impact of the Doppler effect on data transmission. The tests indicated highly reliable data transmission, particularly using a spreading factor of 12, which ensured a 100% packet delivery rate at all tested speeds, while the performance of the spreading factor of 7 proved sensitive to speeds above 35 km/h. Overall, the research conducted in [7] demonstrates the applicability of the Longley-Rice model for predicting signal strength in drone flights, especially in rural agricultural areas.

In the research presented by [5], an artificial neural network (ANN) is proposed for predicting signal strength in drone flights at higher altitudes. Data from regions with varying levels of urbanization were collected using a smartphone attached to a drone, which recorded signal strength and GPS locations at altitudes of 10 m, 18 m, and 24 m, while the drone maintained a fixed speed of 1 m/s.

For ANN development, the data were divided into training (70%), validation (20%), and test (10%) sets. The network was trained to predict ground-level signal strength based on aerial measurements using latitude, longitude, and signal strength (in dBm) as input parameters, with the predicted ground signal strength as the output. The chosen ANN model included two hidden layers with 10 and 7 neurons, respectively. Aiming to optimize the neural network's accuracy and the training process to achieve an MSE of 0.001, the authors opted for a regression approach so that the network's output represents a continuous value of signal strength, classified into four signal coverage quality categories: excellent, good, fair, and poor. The results showed that the ANN successfully predicted ground-level signal strength, achieving an average accuracy of 97%. Additionally, measurements taken at an altitude of 10 m were found to be more accurate than those taken at higher altitudes. The found MSE values were 3.91% for 10 m, 4.20% for 18 m, and 4.51% for 24 m [5].

The study also compared the effectiveness of the neural network in a rural environment and in an open space. The results showed that location influences the accuracy of signal prediction. The MSE was 2.82% in the agricultural location and 2.4% in the open area [5].

The research presented in [6] introduces an artificial neural network model for path loss prediction in urban environments. This approach utilizes a multilayer perceptron, considering activation functions such as the rectified linear unit (ReLU), hyperbolic tangent, and logistic sigmoid.

Data were collected from two urban areas, named Area A and Area B. The neural network configurations included one hidden layer for both hyperbolic tangent and logistic sigmoid activation functions, and up to 8 hidden layers for the ReLU activation function, which proved more stable in deeper networks. Configurations with varying numbers of neurons were tested, and layers with more than 20 neurons showed the most stable performance; thus, 40 neurons were used in the hidden layer. The selected input parameters were frequency (MHz) and distance (m) [6].

In dataset A, the hyperbolic tangent function achieved the best performance, resulting in the lowest RMSE values at frequencies of 3.4 GHz and 5.3 GHz. For the frequency of 6.4 GHz, however, the ReLU activation function showed superior results [6].

The results obtained with the neural network were compared to those from the COST-231 Hata propagation model. Compared to the empirical model, the neural network demonstrated an average improvement of 8.89% and 23.26% in accuracy in Areas A and B, respectively [6].

In the study conducted by [9], a comparative analysis is performed between traditional models (Okumura-Hata, Egli, COST-231, and Ericsson) and an artificial neural network (ANN) model for predicting signal loss in wireless communications involving drones.

The study employs a multilayer perceptron with three nodes in the input layer representing transmitter-receiver distance, transmission power, and altitude. The ANN varies the number of neurons in the hidden layer from 31 to 39 in increments of 2. Nine pairs of activation functions (logsig, purelin, and tansig) are used, resulting in 45 networks for each run of the algorithm, executed 20 times for a total of 900 trained networks. Performance is evaluated using MSE, with weights and biases adjusted for optimization [9].

Results show that for rural routes, the network architecture 9-39-4 (with purelin/tansig activation functions) achieves the lowest MSE of 24.10 dB, while for suburban routes, architecture 1-37-3 (with tansig/purelin functions) obtains an MSE of 8.36 dB. The correlation between ANN-predicted and actual data is 0.75 for rural and 0.95 for suburban environments, indicating superior accuracy in suburban areas [9].

When compared with traditional models, ANN models show superior performance, with RMSEs ranging from 3.96 to 7.07 dB for rural routes and 1.22 to 6.16 dB for suburban routes, surpassing the Egli, COST-231, and Ericsson models [9]. The literature review reveals that most comparative studies on signal strength involving artificial neural networks and conventional propagation models focus on basic models. In this context, a key contribution of this study is the comparative analysis between the Longley-Rice terrain model and the multilayer perceptron, considering terrain characteristics in signal prediction.

III. Methodology

A. Data Acquisition and Preprocessing

Telemetric data for this research project were provided by the C-ISAFE laboratory at CARISSMA of Technische Hochschule Ingolstadt. The Parrot ANAFI AI drone was employed for data acquisition, and flights were conducted in three regions of Germany, ensuring a comprehensive and varied dataset. This project utilized telemetry data from 26 drone flights, with no pauses made during the flights, ensuring that the trajectory covered in each flight was continuous. The flights include the specifications listed in Table I.

TABLE I

Details of the drone flights.

Metric	Rural Region	Suburban Region	Urban Region
Number of samples	14048	12453	13333
Maximum distance traveled (m)	240.64	259.09	578.88
Maximum height (m)	377.57	412.93	389.75
Minimum height (m)	103.73	123.41	108.31

The first step of preprocessing involved filtering outliers from the telemetric data using a quartile statistical methodology. By focusing on the interquartile range (25th to 75th percentile), values outside this central section were considered outliers and excluded to ensure data integrity and accuracy.

To incorporate terrain type information into the neural network, the Copernicus Land Monitoring Service (CLMS), maintained by the European Union, was utilized. NUTS3 codes, which standardize regional statistics in the European Union, were employed in this study. Data from three specific regions identified by the codes DE211, DE219, and DE266 were selected for analysis. Each region exhibits distinct terrain characteristics, contributing to the diversity of the analyzed data.

For calculating the distance d between the controller and the drone, the Haversine function is utilized. Additionally, the altitude of the flight is taken into account for a three-dimensional distance calculation.

$$d = 2R \arctan 2\left(\sqrt{a}, \sqrt{1-a}\right), \tag{1}$$

where:

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right), \tag{2}$$

R is the radius of the Earth (approximately 6,371 kilometers), ϕ_1 and ϕ_2 are the latitudes of the points in radians, $\Delta\phi$ is the difference between the latitudes, and $\Delta\lambda$ is the difference between the longitudes of the two points.

For calculating the distance considering the altitude of the flight, it was considered:

$$d_{3D} = \sqrt{d^2 + \Delta h^2}, \tag{3}$$

where d_{3D} represents the three-dimensional distance and Δh denotes the difference in altitude between the two points.

To minimize the impact of instantaneous power fluctuations, the average value of the signal strength, measured in dBm, was calculated using:

$$\mathrm{Pm} = 10^{\frac{1}{2m+1}\sum_{i=\mathrm{idx}-s}^{\mathrm{idx}+s}\frac{\mathrm{wifi\_signal}_i}{10}}, \tag{4}$$

where idx is the index of the sampled point, s represents half of the sampling interval, m represents the number of observations on one side of the sampled point, ensuring the averaging is performed over $2m+1$ points, k is adjusted to be an odd number to ensure that the average is calculated over a symmetric set of points around idx, and $\mathrm{wifi\_signal}_i$ are the measured power values at the points around the sampled point, covering the interval from $\mathrm{idx} - m$ to $\mathrm{idx} + m$.

B. Flight Route Simulation in Radio Mobile

The simulation process in Radio Mobile starts by establishing the initial geographic point at the drone controller's location, which serves as a reference throughout the simulation. Subsequent points, including latitude, longitude, and altitude information, are then entered into Radio Mobile to simulate the flight route. All sampled latitude and longitude points are used to simulate the communication link, employing the Longley-Rice model for point-to-point prediction.

The flight altitude for each point is calculated by subtracting the terrain elevation above sea level from the point's altitude relative to sea level. The result of this calculation represents the relative height above the terrain that was input for each point in Radio Mobile. Latitude, longitude, and altitude information is present in the telemetry data, while the terrain elevation data are imported into Radio Mobile from SRTM data.

To accurately represent the communication parameters and the drone's specifications, the network properties in Radio Mobile are adjusted, taking into account the technical specifications. The drone's specifications include a transmission power of 20 dBm and a frequency of 2.4 GHz, with both the transmitting and receiving antenna gains set at 3.5 dBi. Additionally, the receiver sensitivity is configured to -94 dBm.

For this research project, three flights were selected in regions with different levels of urbanization to obtain results considering varying levels of signal interference. Subsequently, these same flights will be used in the neural network testing phase to compare the results obtained with the two approaches. The selection criterion for choosing the simulated flight for each region was the flight length, with the longest flight from each region being selected. In this context, the city of Großmehring represents the rural region with a flight length of 240.64 meters, Heustreu is an example of a suburban region with a flight length of 259.09 meters, and Ingolstadt is classified as an urban region with a flight length of 578.88 meters. The classification into types of environments was based on the level of urbanization presented in each of the cities in terms of urban coverage.

Radio Mobile uses the Longley-Rice propagation model to calculate the signal strength at each flight point, recording the Rx Level value in dBm or μV, which indicates the received signal power. The obtained values consider the transmitted signal power, the inherent losses along the signal path, including attenuation due to distance, obstructions, and interferences that can affect signal quality.

C. Multilayer Perceptron

The neural network is structured as a fully connected multilayer perceptron, consisting of three layers: input, hidden, and output. The input layer has ten nodes, while the output layer has a single node corresponding to the Wi-Fi signal strength. A correlation matrix was used to select input parameters for the neural network, aiming to reduce dimensionality and detect multicollinearity among variables. The telemetry data comprises 23 columns of features. After applying the correlation matrix with a threshold of 0.70, the selected features included signal strength data, terrain type ('landcover'), altitude ('gps_amsl_altitude'), elevation angle ('angle_phi', 'angle_psi', and 'angle_theta'), speed ('speed_vx', 'speed_vy', and 'speed_vz'), battery percentage ('battery_percent'), and distance between the drone and the controller ('distance_to_base').

The dataset was partitioned such that 70% (27,884 samples) were allocated for training, 20% (7,967 samples) for validation, and 10% (3,983 samples) for testing. This partitioning also took into consideration the proportions of the regions under analysis, analogous to the methodology employed by [5]. The supervised training of the network utilized the backpropagation method for 500 epochs, in alignment with the research conducted by [5]. Additionally, the early stopping process was implemented to prevent overfitting, stopping the training when the validation loss began to increase after 100 consecutive epochs.

Collecting time-series received signal strength (RSS) observations and averaging them is a common practice to manage RSS fluctuations. However, this approach is compromised by the presence of outliers in the observations, which significantly impact the averaging process and reduce its efficiency. In this regard, the Z-score method, based on the median absolute deviation scale estimator, has been used to detect outliers [8]. For this project, the Z-score normalization was selected to ensure that the impact of outliers is minimized. Additionally, a 3-fold cross-validation technique was used to evaluate the model's performance on different data subsets, reducing overfitting and improving reliability.

The hyperparameter configuration was determined through an exhaustive grid search to identify the optimal parameters that maximize the model's performance. Based on related studies, the tested combinations included the number of neurons in the hidden layer (ranging from 10 to 40), various optimizers (ADAM, SGD, and NAdam), and activation functions (ReLU, Sigmoid, and Hyperbolic Tangent), with learning rates varying between 0.1 and 0.0001. The optimization results for the MLP model indicated that the optimal hyperparameters are 10 neurons in the hidden layer, the ADAM optimizer, a sigmoid activation function, and a learning rate of 0.01.

The training phase of the multilayer perceptron was executed twenty times, and the average values were used to determine the best training and validation loss metrics. After training, the model achieved an average validation loss of 0.24 and a training loss of 0.18. The small difference between these values indicates a strong ability to generalize to unseen data. The weights were randomly initialized, and the Mean Squared Error Loss function was used as the loss function.

To perform inference with the trained neural network, data from the same three flights in rural, suburban, and urban regions, previously used in the simulations employing the Longley-Rice model, were utilized.

IV. Results

For predicting signal strength using the Longley-Rice model and the multilayer perceptron, metrics such as relative error, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used, as these are the main metrics for evaluating neural network performance.

The RMSE calculations was computed as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}, \quad (5)$$

where n represents the total number of observations, Y_i is the actual value of the i-th observation, and $\hat{Y}_i$ is the model's predicted value for the i-th observation.

MAE values are given by:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|, \quad (6)$$

and the relative error was calculated as:

$$\text{Relative Error} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{Y}_i - Y_i|}{|Y_i|}. \quad (7)$$

The results obtained with the simulation in Radio Mobile using the Longley-Rice terrain model are shown in Table II.

TABLE II

Error metrics by region using Longley-Rice model

Region	Relative Error (dB)	RMSE (dB)	MAE (dB)
Rural region	5.05	8.23	6.04
Suburban region	8.16	10.88	8.74
Urban region	11.54	12.84	11.31

The results obtained with the multilayer perceptron are shown in Table III.

Figures 1, 2, and 3 illustrate the results obtained considering the distance between the receiver and the transmitter as a reference.

TABLE III

Error metrics by region using MLP

Region	RMSE (dB)	MAE (dB)
Rural region	1.95	9.89
Suburban region	2.93	7.77
Urban region	2.39	7.99

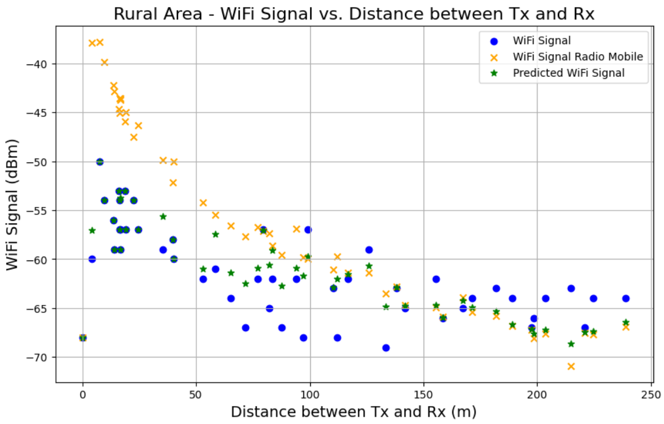

Fig. 1. Signal strength as a function of distance for rural areas.

In the rural region, the results shows the lowest relative error, RMSE, and MAE values among the regions, indicating higher accuracy and smaller deviations in the simulations compared to actual drone flight measurements. The signal strength decreases with increasing distance, as expected, with the Longley-Rice model showing reduced dispersion and consistent results. The MAE is 6.04 dB, reflecting a small average deviation from actual values due to fewer elements causing signal interference in rural areas.

The multilayer perceptron model aligns more closely with the measured values, demonstrating greater accuracy than the Longley-Rice model, especially beyond 100 meters, offering superior correspondence with the measured data.

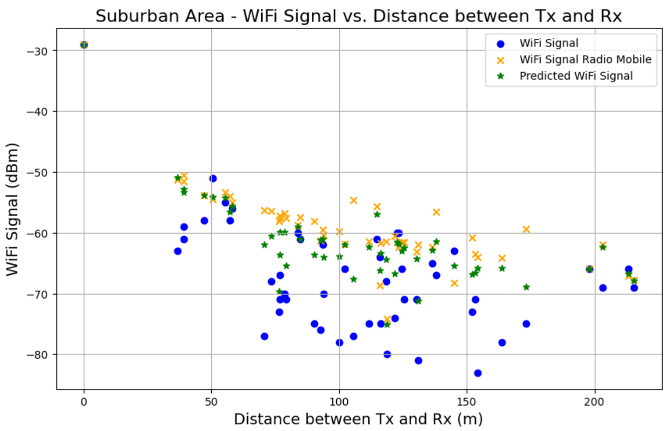

Fig. 2. Signal strength as a function of distance for suburban areas.

In the suburban region, the Longley-Rice model results exhibit intermediate relative error, RMSE, and MAE values when compared to rural and urban areas. Signal strength variations in the suburban area are more pronounced due to increased interference from buildings, vegetation, and varied topography. The Radio Mobile software, utilizing the Longley-Rice model, predicts signal strength trends that generally follow the actual drone measurements, albeit with some discrepancies arising from model assumptions and simplifications. Conversely, the multilayer perceptron predictions align more closely with the actual drone measurements, demonstrating superior accuracy.

The actual drone measurements exhibit greater variability due to environmental factors like buildings and trees, which cause signal reflections and scattering. Overall, the multilayer perceptron model provides predictions that match the actual data more closely than the Longley-Rice model, suggesting its better suitability for the suburban environment.

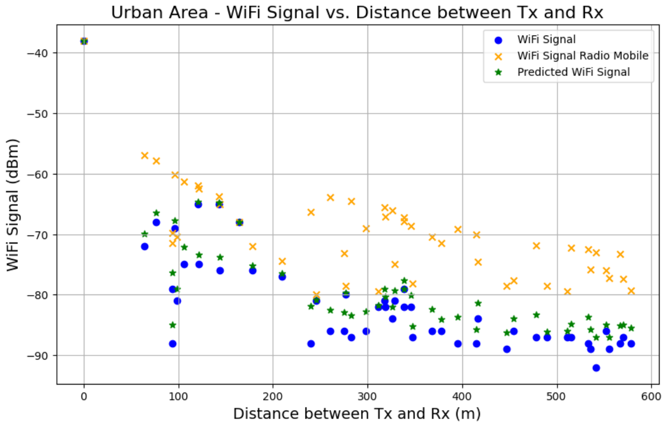

Fig. 3. Signal strength as a function of distance for urban areas.

In the urban region, signal strength declines gradually with distance due to the consistent influence of urban topography. Radio Mobile's predictions significantly differ from actual drone measurements, highlighting the Longley-Rice model's limitations in urban settings. Environmental factors like buildings and trees cause considerable variability in measured signal strength. While Radio Mobile's model indicates a decrease, it often overestimates values, especially beyond 100 meters. The multilayer perceptron model aligns more closely with actual measurements, accounting better for urban variables and providing more realistic WiFi signal strength predictions. Despite slight overestimations, it is more reliable for practical applications in urban areas.

The comparative analysis between WiFi signal strength prediction models reveals that the multilayer perceptron model aligns more closely with the real values measured by drones compared to the Longley-Rice model. While the Longley-Rice model tends to overestimate signal strength, the multilayer perceptron model shows a more accurate correspondence with the real measurements, despite also displaying a slight tendency to overestimate.

The real drone measurements exhibit significant variability due to interferences and obstructions such as buildings and trees, which are not fully captured by the predictive models. Therefore, the multilayer perceptron model is more suitable for predicting WiFi signal strength in the three regions, as it better captures the complexities and environmental variations typical of the analyzed areas, adjusting more precisely to the changes in signal strength caused by physical obstacles and interferences present in the environment.

V. Conclusion and Future Work

The observed discrepancies between the outcomes generated by the Longley-Rice model and the telemetry data acquired from drone flights underscore the necessity for developing more precise methodologies for predicting signal strength during drone operations. In this regard, artificial intelligence techniques emerge as a promising alternative for such predictions. The RMSE values obtained indicate that the Longley-Rice model consistently overestimates received power, inadequately accounting for signal interferences and obstructions.

Future research should focus on acquiring a more robust and diverse dataset to improve the multilayer perceptron algorithm's generalization. Additionally, exploring machine learning methods like Random Forest and Support Vector Machine could be beneficial in high-noise scenarios. Another promising direction is using the signal strength prediction algorithm to optimize and predict drone flight trajectories, enhancing resource utilization and energy efficiency in UAV operations.

Aknowledgements

The authors would like to thank the Bayerische Hochschulzentrum für Lateinamerika (BAYLAT) for the financial support, which significantly contributed to the research conducted for this paper.

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