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Path Loss Prediction using Artificial Neural Networks in UHF TV Channel at Uberlândia/Brazil

Predição de Perda de Percurso utilizando Redes Neurais Artificiais em um Canal de TV UHF em Uberlândia/Brasil

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ABSTRACT

This article presents a new model for the prediction of electromagnetic wave propagation. In order to reach the goal of this study, the signal strength received in the frequency of 569 MHz on the UHF band was measured in the city of Uberlândia (Brazil). From these measurements, the calculation of path loss was performed, and an Artificial Neural Network (ANN) was developed, which possesses the ability to predict such phenomenon. The results obtained by this neural network demonstrated superior results when compared to other models, such as Free Space Loss Recommendation ITU-R P.1546-6, Hata, Egli, COST 231 and ECC-33. The results obtained, using the proposed model, were also superior to those obtained using models presented in the most recently published literature. Through use of the presented model, a statistical analysis was performed, which obtained the following results 2.23-dB Mean Absolute Error, 8.287-dB Mean Squared Error, 2.879-dB RMS Error, 1.82-dB Standard Deviation and 93.6% Coefficient of Determination.

Keywords: Artificial Neural Networks; Levenberg–Marquardt; Path loss; Propagation; UHF.

RESUMO

Este artigo apresenta um novo modelo para a previsão da propagação de ondas eletromagnéticas. Para atingir o objetivo deste estudo, a intensidade do sinal recebido na frequência de 569 MHz na banda UHF foi medida na cidade de Uberlândia (Brasil). A partir dessas medições, foi realizado o cálculo da perda de caminho e desenvolvida uma Rede Neural Artificial (RNA), que possui a capacidade de prever tal fenômeno. Os resultados obtidos por esta rede neural demonstraram resultados superiores quando comparados a outros modelos, como a Recomendação de Perda de Espaço Livre ITU-R P.1546-6, Hata, Egli, COST 231 e ECC-33. Os resultados obtidos, com o modelo proposto, também foram superiores aos obtidos com os modelos apresentados na literatura publicada mais recentemente. Através da utilização do modelo apresentado, foi realizada uma análise estatística, que obteve os seguintes resultados 2,23-dB Erro Médio Absoluto, 8,287-dB Erro Médio Quadrado, 2,879-dB Erro RMS, 1,82-dB Desvio Padrão e 93,6% de Coeficiente de Determinação.

Keywords: Levenberg-Marquardt; Perda de Percurso; Propagação; Redes Neurais Artificiais; UHF.

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INTRODUCTION

The propagation of radio waves has long held a significant importance in the field of research and development concerning broadcasting. As such, over time, several models have been developed and improved, thus making these simpler and more precise, where such have been incremented with the means to predict the coverage area of the transmission setup and optimise the performance of the broadcasting links (AYADI, BEN ZINEB, TABBANE, 2017).

Propagation models are widely used in the planning of broadcasting systems, allowing, as such, for the prediction of interference levels and facilitating feasibility and management studies during the implementation process of the system. As the electromagnetic wave travels through space, attenuation occurs due to various influences.

These models are used to predict the Path Loss (PL) at a given location in each environment. PL is the attenuation of the signal from transmitter to receiver during transmission (MALOKU, FAZLIU, et al., 2019). In other words, this can be understood as the energy consumption that occurs between the transmitting antenna and the receiving antenna (FENG, BOZHANG, et al., 2015). The PL is affected by several factors, those being base station height, diffraction, refraction, free space loss, urban profile, terrain altitude levels, absorption, among others (FANAN, RILEY, et al., 2016).

Incidentally, PL can be considered a regression problem. In regression problems, it is necessary to have input and output parameters. Input parameters are transmitter information, receiver, building height, frequency, among others. Output parameters are represented by propagation loss. The goal of regression is to find a function via the input parameters that estimates output (AYADI, BEN ZINEB, TABBANE, 2017).

The aim of the present paper is to collect received signal strength data from the UHF signal in the frequency band of 566-572 MHz (Channel 30 according to Brazilian Agency of Telecommunications), in the city of Uberlândia (Brazil) and then compare the measured values with the theoretical values obtained from propagation models. The models used for analysis are ITU-R P.1546, Hata, Egli, Cost 231 and ECC-33 and a model that will be developed based on Artificial Neural Networks (ANN). In addition to comparisons with other prediction models, a comparison will also be made with studies that incorporate ANN to calculate PL.

LITERATURE REVIEW

Many researchers have developed articles using neural networks to calculate the PL. The study conducted by Ayadi, Ben Zineb,Tabbane (2017) collected data in Tunis (Tunisia) at 450, 850, 1800, 2100, and 2600 MHz bands. These authors split the measurements randomly into two sets. The first set was used for training and the second for model validation. These authors use a backpropagation (BP) algorithm with one hidden layer that obtains its inputs from the Standard Propagation Model; this possesses additional parameters such as frequency, environment type, land use distribution, and diffraction loss. The new model demonstrated a significant difference in comparison to the ITU-R P1812 model, when predicting receiver signal strength.

The collaborators in Popoola, Faruk, et al.(2019) collected the data in Ilorin (Nigeria) in an urban environment and characterised the propagation path loss using the received signal strength on a VHF band at the frequency of 203.25 MHz. The developed ANN had one hidden layer with 80 neurons; the input was established as the prediction computed from the Hata, COST 231, ECC and Egli models, along with the distance between the transmitter and the receiver. The ANN was trained using Levenberg-Marquardt (LM) and Scale Conjugate Gradient (SCG). The conclusion reached was that the prediction errors for all the ANN algorithms were superior to those of the empirical models.

Research by Popescu, Nafomita, et al. (2001) presents neural network-based models for the prediction of propagation path loss in an urban environment. Measurements of field strength were collected in Kavala (Greece) at the frequency of 1890 MHz Two kinds of neural networks were designed. The first one for line-of-sight (LOS) cases and second for non-line-of-sight (NLOS) cases. The performance of the neural models was compared to those of the COST231-Walfisch-lkegami model, the Walfisch-Bertoni model and the single regression model. The authors concluded that the ANN significantly improved the prediction of PL when compared to empirical models, this due to their ability to perform an interpolation or an extrapolation if the test pattern exceeds the training pattern space. Another advantage in the use of neural networks is that these are trained with measurements and, as such, the auxiliary propagation effects become more realistic.

The study by Benmus, Abboud, Shatter (2015) collected a relatively good number of measurements from different places in the capital of Libya, Tripoli. The received signal strength at a distance between 0 to 1 km range from the transmitter, at frequencies of 900 MHz, 1800 MHz and 2100 MHz, was used to develop a new model using a Neural Network approach. The model proposed in Benmus, Abboud, Shatter (2015) was tested and provided an acceptable accuracy over the results. The values of received signal strength obtained from this model were compared to other values obtained when applying the Hata model. The results obtained from this work are considerably closer to real measurement data.

The researched performed by Eichie, Oyedum, et al.(2017) acquired data in a drive test through selected rural and suburban areas in Minna (Nigeria) and developed an ANN based path loss model. The parameters collected were distance between transmitting and receiving antennas, transmitting power and terrain elevation using sea level as reference point at a frequency of 1800 Mhz. These parameters were used at the input of a Multilayer perceptron network. The developed ANN based path loss model demonstrated a superior performance than those of the Hata, Egli and Cost-231 models.

The collaborators in Cheerla, Ratnam, Borra (2018) implemented an ANN MLP-based model with 10 hidden layers, which was trained using the Levenberg-Marquardt algorithm. The data was collected in Vijayawada, India at frequencies of 800 and 1800 MHz. The inputs of the ANN were frequency, width of roads, building separation, height of transmitter, orientation angle, distance (between transmitter and receiver), elevation (of receiver) and target (difference between the COST 231 model prediction and real-time PL collected). The authors concluded the ANN model prediction accuracy was superior to all existing path loss models.

Research conducted in Ferreira, Matos, Silva (2016) measured signal strength at 1140 MHz in an urban environment, in Rio de Janeiro, Brazil. The measurements were compared to those from more common methods, such as Cascade Knife Edge and Delta Bullington. An ANN was used to improve the typical predictions. This ANN used the following as input distance, diffraction loss and signal prediction. The authors concluded that the ANN had contributed toward the improvement of radio frequency coverage prediction.

The study conducted in Park, Tettey, Jo (2019) developed an ANN based multi-dimension regression framework in order to learn from the path loss data, which is a function of distance and frequency. The frequencies used was 3 to 6 GHz in an urban environment. An analysis was made concerning the effect from the architecture parameter, as in the activation function, number of hidden layers and prediction nodes. The proposed model obtained more accurate and flexible results than those of the conventional linear model.

The focus of the study in Sotiroudis, Siakavara (2015) was to obtain a PL prediction with sufficient accuracy, while using an ANN using a low quantity of data but of an adequate type. The network input information is the terrain profile of the propagation environment, while the data provided is of minimal quantity. The proposed ANN technique was validated as effective for estimating the PL of the transmitted signal after a comparison was made of the analytical results and theoretical methods.

The study conducted herein used the city of Uberlândia/Brazil for field measurements since there is a demand for research in this area. The city has 15 television stations operating in the UHF band; in addition, the city is of a medium size with almost 700 thousand inhabitants, as well as being situated among the 30 largest GDPs in Brazil (BRAZILIAN INSTITUTE OF GEOGRAPHY AND STATISTICS (IBGE), 2019). Comparing the aforementioned studies, with respect to the training algorithm employed, Ayadi, Ben Zineb, Tabbane (2017) used Gradient Descent, while this study used Levenberg-Marquardt, which demonstrates a faster convergence rate. In relation to distance range, this study used from 0 to 8.12 km, while for Popescu, Nafomita, et al. (2001), Benmus, Abboud, Shatter (2015), Eichie, Oyedum, et al.(2017), Cheerla, Ratnam , Borra (2018) a shorter range was employed. This study performed several training sessions with different quantities of neurons in the hidden layer starting at 10 neurons and increasing from 10 to 200. This was performed in order to verify in which setup the network presents better performance, while maintaining the generalization capacity and avoiding overfit, Eichie, Oyedum, et al.(2017) trained the ANN from 10 to 30 neurons, Ferreira, Matos, Silva (2016) trained the ANN from 31 to 39 neurons, on the other hand studies Popoola, Faruk, et al. (2019), Popescu, Nafomita, et al. (2001) and Sotiroudis, Siakavara (2015) used a fixed quantity of neurons in the hidden layer. Concerning the range of frequency, Popoola, Faruk, et al. (2019) uses VHF band, however, these frequencies are no longer used in television, as the process of television broadcasts in Brazil is now digital, Popescu, Nafomita, et al. (2001), Benmus, Abboud, Shatter (2015), Eichie, Oyedum, et al.(2017), Cheerla, Ratnam, Borra (2018) and Sotiroudis, Siakavara (2015) used frequencies for mobile communications. These are designed to cover cells with short distances by contrast this study used a frequency in a UHF band used on television broadcasts that are designed to cover the area covered by various municipalities or even metropolitan regions. Additionally, this work possesses as a differential the presentation of a table Table 2 in which several parameters that characterise a neural network design and their respective errors are presented. This accumulated in the best design that minimises the error and at the same time maintains the general potential for future work with measurements at different points as entry into the region. Additionally, a more complete statistical analysis was performed than in other studies, as calculations were performed for Mean Absolute Error (MAE), Mean Squared Error (MSE), RMS Error (RMSE), Standard Deviation (σ) and Coefficient of Determination (R^2).

PROPAGATION MODELS

Free Space Path Loss

Free Space Loss can be defined as the difference between the power transmitted by an isolated point source and the power received between two points in the free space environment with no obstacles between them (MOLLEL, KISANGIRI, 2014). The calculation for Free Space Loss is as follows:

$$L = 32{,}46 + 20\log(d) + 20\log(f) \tag{1}$$

Where:

-L is the quantity of signal strength lost during propagation (dB).

-f is the frequency (MHz).

-d is the distance (km).

In practice, free space loss can be used for point-to-point links if there is no atmospheric phenomenon such as clouds and there is no obstacle.

Hata Model

The Hata model was developed to predict PL in outdoor environments, for distances between 1 to 20 km and frequencies between 150 MHz to 1500 MHz (HATA, 1980). This model was developed from the experimental curves of the Okumura model, from these curves Hata developed expressions to approximate the curves (2), thus allowing for facilitated computational use (MOLLEL, KISANGIRI, 2014).

$$\begin{gathered} L = 69{,}55 + 26{,}16\log(d) - 13{,}83\log(h_t) \\ -a(h_r) + (44{,}9 - 6{,}55\log(h_t))\log(d) \end{gathered} \tag{2}$$

Where:

$-h_t$ and h_r are respectively the height of the transmitting and receiving antennas (m).

$-a(h_r)$ is the correction factor for the effective height of the receiving antenna.

The factor $a(h_r)$ depends on the dimensions of the municipality where the prediction will be made. Uberlândia can be considered a much smaller city than the city of Tokyo, where measurements were made for the development of this model. For this reason, the correction factor given by (3) for small cities was used.

$$a(h_r) = (1{,}1\log(f) - 0{,}7)h_r - (1{,}56\log(f) - 0{,}8) \tag{3}$$

Egli Model

John Egli developed this model in 1957. In his study, land data is used which was collected by commercial organizations from several cities across the United States. In each of these cities, he performed electric field strength measurements to formulate his model. To make a simple model, Egli assumed that all terrains are slightly undulating; these undulations possessed a maximum amplitude of 50 feet, that is, 15.34 meters. The prediction can be performed using this model for distances up to 60 km and frequencies between 40 MHz and 1000 MHz (EGLI, 1957).

$$L = \begin{cases} 20\log(f) + p_0 + 76{,}3 & if\ h_r < 10 \\ 20\log(f) + p_0 + 85{,}9 & if\ h_r > 10 \end{cases} \tag{4}$$

$$p_0 = 40\log(d) - 20\log(h_t) - 10\log(h_r) \tag{5}$$

Cost 231 Model

The Hata model is limited to frequencies of up to 1500 Mhz. To overcome this limitation, the COST cooperation modified the Hata model and developed a new model also called Hata Model PCS Extension, thus opening the possibility to predict the PL for frequencies of up to 2000 MHz.

$$L = 46.3 + 33.9log(f) - 13{,}82log(h_t) \\ -a(h_r) + c - 44.9 - 6.55log(h_t)log(d) \tag{6}$$

For urban environments, the parameter c that is used must be equal to 0 dB, while for urban environments, the value used must be equal to 3 dB (MOLLEL, KISANGIRI, 2014).

The parameter $a(h_r)$ defined for urban parameters, which is the case of the city of Uberlândia, takes the following form:

$$a(h_r) = 3.2\left(log\ (11.75h_r)\right)^2 - 4.94 \tag{7}$$

ECC-33

The measurements made by Okumura that led to the development of the Hata model were carried out in Japan, where the characteristics of buildings and urbanism are very different from European cities. In the ECC-33 model, extrapolations in the Hata model were performed to calculate the PL for frequencies of up to 3.8 GHz. In addition, city size classifications were changed to suit the European reality (ABHAYAWARDHANA, WASSELL, et al., 2005)

$$L = A_{fs} + A_{bm} - G_b - G_r \tag{8}$$

Where:

-A_{fs} is the free space attenuation.

-A_{bm} is the basic mean PL.

-G_b is the height gain factor of the transmission antenna.

-G_r receiving antenna gain factor

In (8)-(12), one finds the expression for calculating the aforementioned factors

$$A_{fs} = 92.4 + 20\log(d) + 20\log\ (f) \tag{8}$$

$$A_{bm} = 20{,}41 + 9{,}83\log(d) + 7{,}89(f) + 9{,}56(\log(f))^2 \tag{9}$$

$$G_b = \log\left(\frac{h_t}{200}\right)(13{,}958 + 5{,}8\log(d))^2 \quad (10)$$

The expressions for medium-sized and large-sized cities are respectively (11) and (12).

$$G_r = (42{,}57 + 13{,}7log(f)(log(h\_r) - 0{,}585) \quad (11)$$

$$G_r = 0{,}759h_r - 1{,}862 \quad (12)$$

Where:

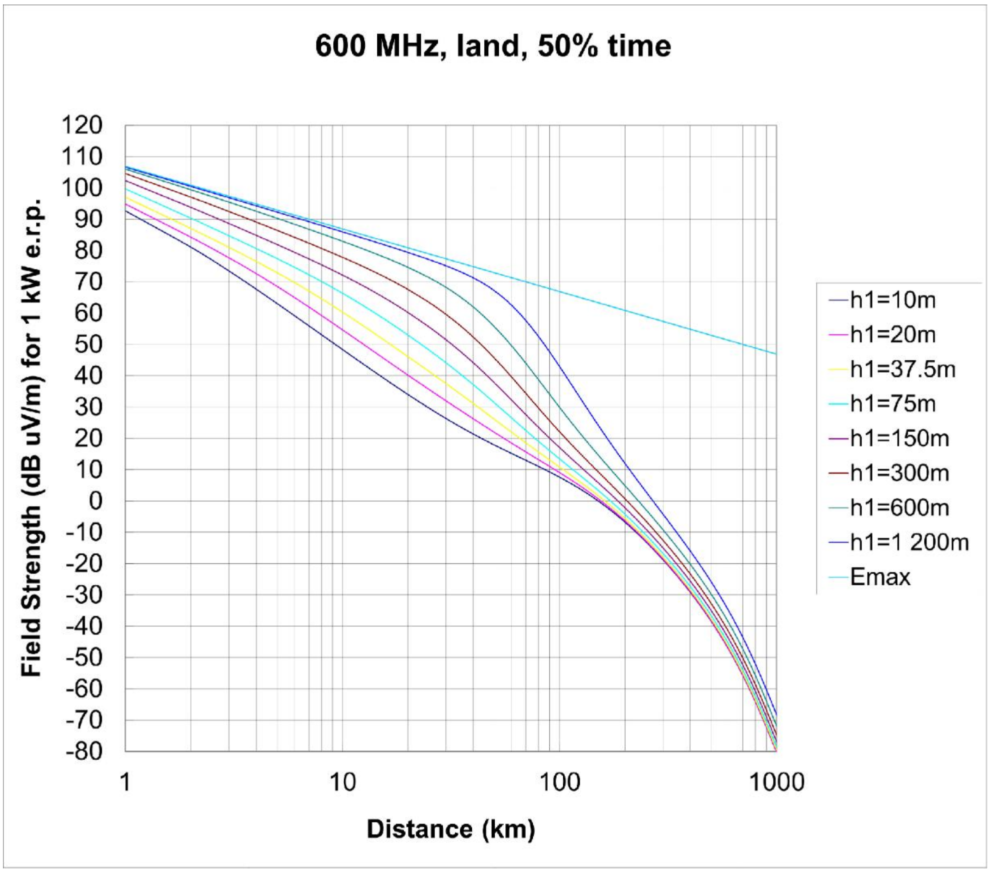
-f in (GHz).

The midsize city model is more appropriate for Uberlândia, while the large city environment should only be used for cities with high-rise buildings (MOLLEL, KISANGIRI, 2014).

ITU-P.1546 Recommendation

This recommendation was developed by the International Telecommunications Union (ITU) from curves obtained through measurements made at the nominal frequencies of 100, 600 and 2000 MHz. This model can be used to predict PL for distances of up to 1000 km and a transmitting antenna with height of up to 3000m in both environments land and sea, or mixed environments and through interpolation and extrapolations. This can be used in the frequency range between 30 MHz up to 3000 MHz, that is, the VHF and UHF frequency bands. Figure 1 illustrates a curve for various antenna altitudes for the 600 MHz frequency on a terrestrial path for 50% of the time. Also in the recommendation are corrections that can be applied to environments or situations where measurements were not made.

Figure 1 - Experimental curves used in Model ITU-P.1546



Source: International Telecommunication Union (2022)

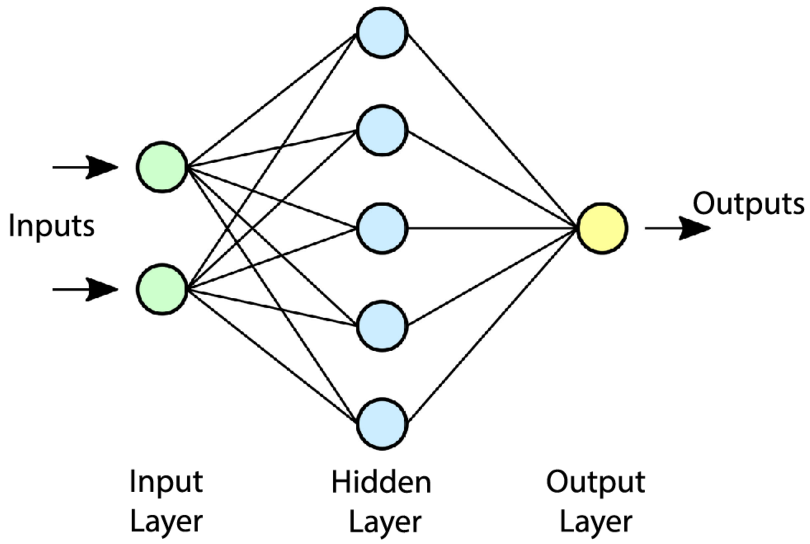
The ITU has a study group, called Study Group 3 (SG 3), which makes available on its web page the code in function format for Matlab software for the computational calculation of PL (ITU-R RECOMMENDATION ITU-R P.1546-6, 2019).

ARTIFICIAL NEURAL NETWORKS

ANN is a computer program that simulates the way the human brain processes information, through units that perform in parallel, which work in a similar way to the brain, in order to perform a given task. This unit (neuron) as well as the biological neuron, receives the input signals, these input signals are weighted by weights (which represent knowledge) and then all the weighted signals are added. Following this, this summation passes through a non-linear activation function to produce a given output response (HAYKIN, 2009).

The units can be connected to each other in the form of layers, Figure 2, that is, the output of one becomes the input of another. The arrangement in the form of layers gives an ANN the ability to perform regressions (linear and non-linear), recognise patterns, perform classifications, among others.

Figure 2 - Architecture of ANN



Source: The Authors (2022).

The analytical expression of how each output k of an ANN is demonstrated in (13).

$$y_k = F_o\left(\sum_{j=1}^{K} W_{kj}\left(\sum_{i=1}^{N} W_{ji}x_i\right)\right) \tag{13}$$

Where:

- W_{kj} represent the weights of neuron j in the hidden layer for the output neuron k.

- W_{ji} represent the weights between the input layer and hidden layer neurons.

- x_i represents the i-th neuron at the input layer.

- F_h represents the activation functions of the hidden layer.

- F_o represent the activation functions of output layer.
- y_k is the output k of the ANN.

It is necessary first to train the ANN before using it, that is, adjust the weights so that the output of the neural network offers a satisfactory response to the desired pattern.

In other words, the network is "shown" which output is desired for each input, and the weights are updated so that the network output becomes closer to that desired. In a multi-layer ANN, training was only possible through the development of the BP algorithm, which is considered a revolution in neural networks. In this algorithm, the updating of weights is performed through the Gradient Descending method; the weights are updated so that the MSE, in (14), is minimised.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - d_i)^2 \tag{14}$$

Where:

- y_i is the output value calculated by the ANN.
- d_i represents the desired output value of the network.

In addition to the Gradient Descending method, other algorithms can be used to update the weights of an ANN. For example, the algorithm called Levenberg-Marquardt (LM), which modifies the Gradient Descending algorithm, providing greater agility in certain cases, which in general can be between 10 to 100 times (HAGAN, MENHAJ, 1994).

In a data collection process, noise, or measurement inaccuracies on the part of the equipment is a common occurrence, due to this fact, the data presented to the network, input, and output data, will also be influenced by this noise. To overcome this problem, it is necessary that the training of the network is of a generic nature, that is, it presents satisfactory outputs for inputs that were not trained (POPESCU, NAFOMITA, et al., 2001). One way of fulfilling this objective is to separate the input data into three groups, the training group, validation group, and testing group (MATLAB, 2018). The training and validation groups are used during the training phase; the difference is that to adjust the data only the training group is used. The validation group serves to verify if the network remains generic during the training stage. The test group is used after training to confirm that, after training, the network is still generic to data that were not used for training.

METHODOLOGY

The first part of the method put forward in this study was the definition and description of the transmission and reception system. The transmission system is in Umuarama district, in the north sector of Uberlândia. This system is comprised of a transmitter, transmission line and a radiating system; the characteristics of the system are described in Table 1.

Table 1 - Irradiant System Characteristics

Frequency Range	566 a 572 MHz
Carrier Frequency	569.142857 MHz
Transmitter Power	2.5 kW
Antenna Model	ISDE083022UT
Beam-tilt	4º
Azimute	210º
Polarization	Elliptical (70x30)
Transmitter	13.3484 dBi (Horizontal)
Antenna Gain	9.6684 dBi (Vertical)
Center Irradiation Height	64 m
Transmission Line Model	HCA158-50J
Transmission Line Length	71 m
Vertical beamwidth of transmitting antenna	6.5º
Other Loss	1.27 dB

Source: Brazilian Agency of Telecommunications (Anatel) (2022)

The reception system (Figure 3) is composed of two omnidirectional vertical antennas with 0 dB gain, a device with a satellite navigation system that uses the American Global Positioning System (GPS), a TSMW model coverage analyser manufactured by the company Rhode & Schwarz and a laptop with Romes software coupled to the coverage analyser.

Figure 3 - Reception System

Source: Rhode & Schartwz (2019, p.15)

The ROMES software was configured to record samples of received signal strength (RSS) at the carrier frequency (569.142857 MHz). Figure 4 shows the route travelled by a car, and along which samples were recorded. For analysis purposes, the resultant is considered for each geographic coordinate and is calculated as the arithmetic mean between the RSS measured by antennas 1 and 2 (17). If a given geographic coordinate has more than one RSS, the arithmetic mean is first calculated for Antennas 1 (15) and 2 (16) and then the resultant RSS is established by (17).

$$RSS_1 = \frac{\sum_{i=1}^{N} RSS1_i}{N_{(lat,lon)}} \tag{15}$$

$$RSS_2 = \frac{\sum_{i=1}^{N} RSS2_i}{N_{(lat,lon)}} \tag{16}$$

$$RSS_t = \frac{RSS_1 + RSS_2}{2} \tag{17}$$

Where:

$-RSS_1$, $RSS1_i$ of antenna 1.

$-RSS_2$, $RSS1_2$ of antenna 2.

$-N_{(lat,lon)}$, number of samples in the same geographic position.

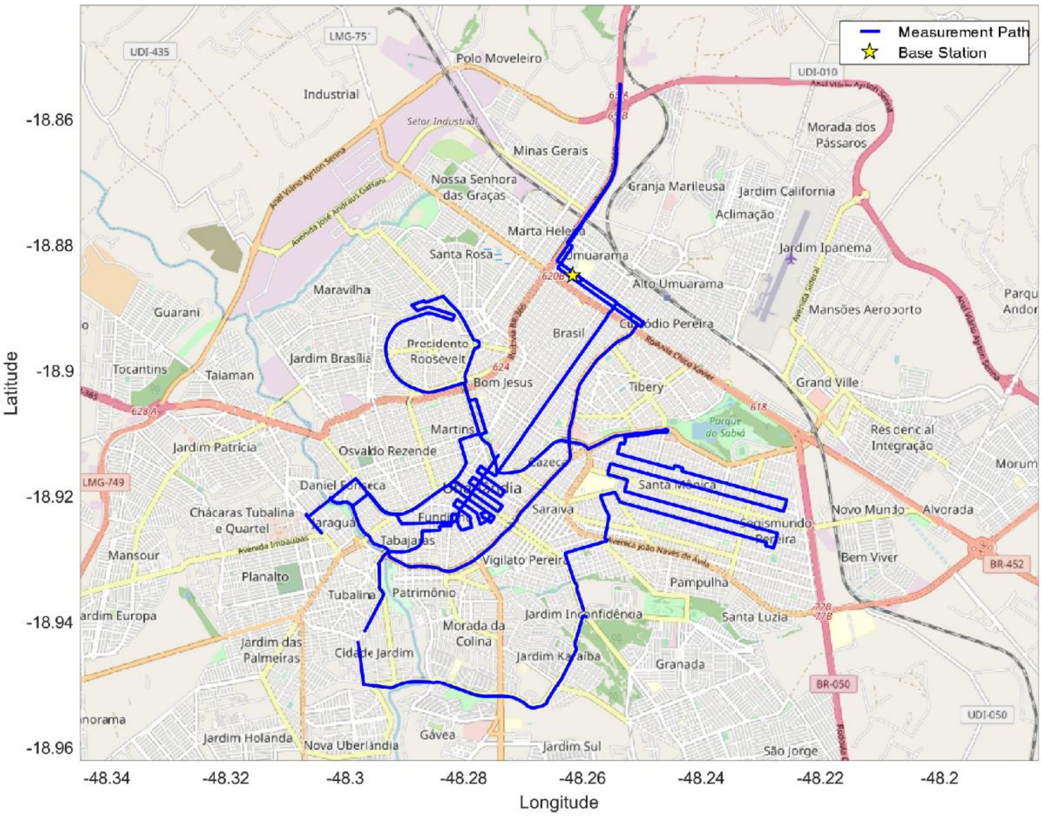
$-RSS_1$, mean of all $RSS1_i$.

$-RSS_2$, mean of all $RSS2_i$.

$-RSS_t$, mean between RSS_1 and RSS_2.

The samples numbered as 102,590 resulted in 9,319 electrical power samples, which resulted in a new database as illustrated in the path in Figure 4.

Figure 4 - Measurements Path and Base Station Location



Source: The Authors (2022)

Each of the samples in the new database is stored and for which the PL needs to be calculated. The calculation was performed using (18) (FANAN, RILEY, et al., 2016). From Table 1, the value to be used by the transmitting antenna was 2.5 kW multiplied by 0.3, due to vertical polarization. Therefore, the value of P_t used was 57.48, which had been previously converted into dBm, with the subtraction of the other losses (1.27 dB) from the transmitter. The value of G_t used was equal to 9.6684 dB, which corresponds to the value for vertical polarization. The values of RSSr were used with each one of the 9,319 samples of RSS. As the coverage analyser antenna has unity gain, the G_r has its value equal to 0 dB.

$$PL_{(dB)} = Pt_{(dB)} + Gt_{(dB)} - Pr_{dB} - Gr_{(dB)} \quad (18)$$

Where:

$-PL_{(dB)}$ is the PL value.

$-Pt_{(dB)}$ is the transmitter power value.

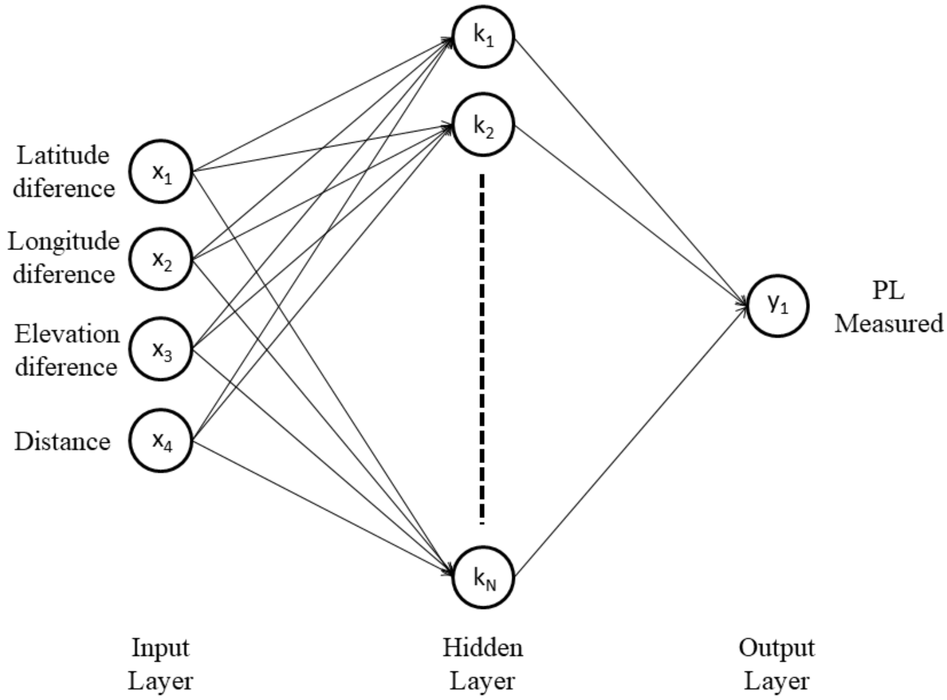
$-Gt_{(dB)}$ is the gain of the transmitting antenna.

$-Pr_{dB}$ is the RSS obtained by the reception system.

$-Gr_{(dB)}$= 0 dB, which is the gain of the antenna coupled to the receiver.

Following this the ANN was developed. According to the new database, an analysis of the parameters was carried out to define the inputs and outputs of the ANN. Other factors affect the PL, however, in this paper we consider four parameters as input, those being latitude, longitude and elevation difference (between BS and sample), and distance. The use of the difference in some input variables aims to make the ANN generic and can be used to simulate the PL in other locations; this can be achieved simply by adding the latitude, longitude, and elevation of the location BS. The output is the PL calculated in (18). The ANN developed in this paper is illustrated in Figure 5.

Figure 5 - ANN developed architecture



Source: The Authors (2022)

The network was trained using Matlab software, through its Neural Net Fitting toolbox. The distribution for training, validation and testing was defined using respectively sample sets of 6,523 (70%), 1,398 (15%) and 1,398 (15%).

The next step is choosing the number of neurons in the hidden layer. The choice was made empirically by performing the ANN training, with different numbers of neurons, starting with 10 neurons, increasing by 10 to 200 neurons. After training the different numbers of defined neurons, the MSE results were found for the training series as demonstrated in Table 2.

Table 2 - Result of Training for Different Numbers of Neurons in the Hidden Layer

Hidden Layer Neurons	Training MSE (dB)	Validation MSE (dB)	Test MSE (dB)	Overall MSE (dB)
10	17.670	18.090	16.904	17.584
20	11.796	13.873	13.110	12.644
30	9.787	10.415	10.044	10.008
40	9.404	10.473	10.329	9.903
50	9.228	10.897	10.372	9.931
60	8.912	10.697	10.037	9.639
70	8.769	10.325	10.328	9.548
80	8.271	10.845	10.386	9.443
90	9.165	10.751	11.449	10.133
100	9.619	10.421	10.520	10.044
110	9.455	11.184	11.456	10.387
120	9.538	12.228	10.474	10.445
130	8.279	10.567	11.096	9.555
140	8.352	10.222	10.765	9.423
150	8.761	10.065	9.997	9.396
160	**8.002**	**8.796**	**9.700**	**8.376**
170	7.924	9.522	10.164	8.883
180	8.285	10.242	11.110	9.481
190	7.890	11.296	10.292	9.342
200	7.905	10.207	13.302	9.830

Source: The Authors (2022).

From the values in Table 2, a hidden layer with 160 neurons was chosen as this configuration presents the lowest value equal to 8.376 dB from the Overall MSE among all those tested. Noted here also was that with more than 160 neurons in the hidden layer, the MSE training values were lower than with 160 neurons. However, the MSE validation and MSE test values were higher, which indicates that the network lost the ability to generalise for these quantities of neurons.

Considering the development of the ANN with 160 neurons, the next step is to develop the propagation models script in Matlab (ITU-R P.1546, Hata, Egli, COST 231, ECC-33 and ANN) to calculate and compare the values of PL of the samples with the theoretical values obtained.

The performance evaluation of an ANN was measured using the following statistical metrics MSE, for which the formula is described in (14), MAE, RMSE, σ and R^2. The formula of these last four are described below through (19)-(22), the Mean Error (ME) was not calculated due to the fact that positive and negative errors cancel each other.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(PL_i^{measured} - PL_i^{predicted}) \quad (19)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(PL_i^{measured} - PL_i^{predicted}\right)^2} \quad (20)$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(|PL_i^{measured} - PL_i^{predicted}|\right)^2 - \mu} \quad (21)$$

where, μ = the mean prediction error in decibel (dB).

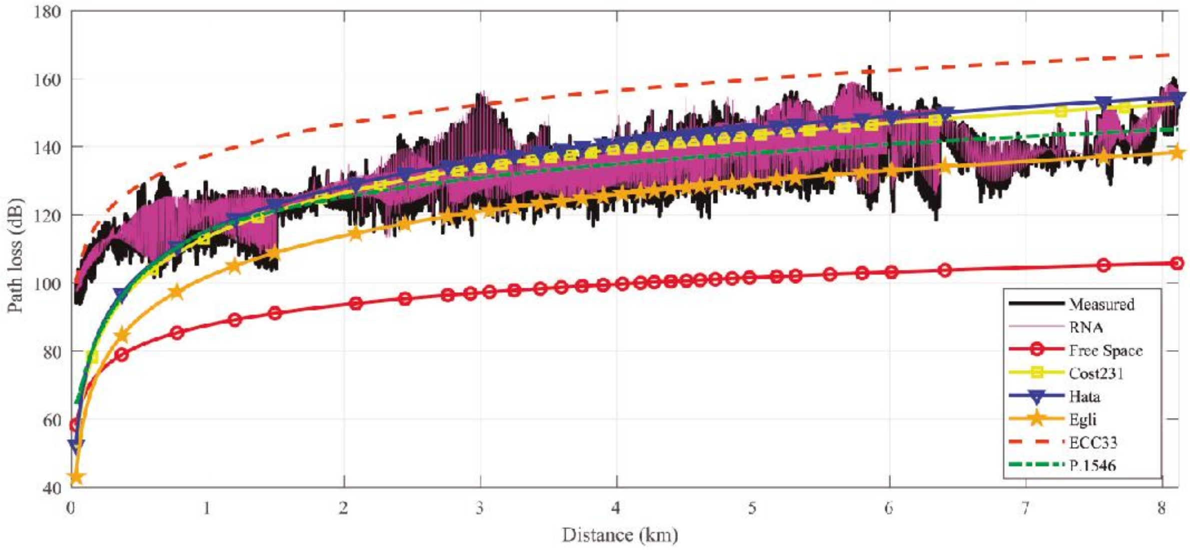
$$R^2 = \frac{\sum_{i=1}^{N}\left(PL_i^{measured} - PL_i^{measured\ mean}\right)^2 - \sum_{i=1}^{N}\left(PL_i^{predicted} - PL_i^{measured}\right)^2}{\sum_{i=1}^{N}\left(PL_i^{measured} - PL_i^{measured\ mean}\right)^2} \quad (22)$$

RESULTS AND DISCUSSION AND DISCUSSION

Comparison with other PL prediction models

The graphical comparison between PL obtained based on the developed ANN model and the chosen theoretical propagation models is illustrated in Figure 6

Figure 6 - ANN model with FSL, Cost 231, Hata, Egli, ECC-33 and ITU-P.1546



Source: The Authors (2022)

One notes from Figure 6 that the prediction of the ANN model follows the measurement curve, as it provides the best fit along the way. The COST 231, Hata and P.1546 models presented satisfactory results regarding loss prediction. While the Egli model, although still following the measured values, presented an underestimation of the loss, as well as the Free Space Loss model that was considerably underestimated with respect to the measurements. On the other hand, the ECC-33 model for the measured region overestimated the loss along the propagation path. To verify the statistical behaviour of the PL, the calculations of σ, MAE, MSE, RMS Error, R^2 are performed as shown in Table 3.

Table 3 - Comparison of metrics between PL models and ANN

Model	MAE	MSE	RMSE	σ	R^2
Free Space	36.854	1.410.354	37.555	7.223	0.626
ECC-33	19.135	414.321	20.355	6.942	0.644
Egli	12.728	228.401	15.113	8.149	0.626
Hata	7.096	93.124	9.65	6.54	0.626
Cost 231	6.558	86.503	9.301	6.596	0.626
ITU P.1546-6	6.423	75.138	8.668	5.821	0.602
This Work	2.23	8.287	2.879	1.82	0.936

Source: The Authors (2022)

Comparison between other studies

The use of ANN models has seen an increase in the number of studies applying such technology. In the Table 4 some recent papers on the subject are presented, this table contains the place where the study was performed, the frequency, the training algorithm and the performance metrics used in these studies. The performance metrics that were not presented prior but that are encountered in the table are Maximum Error (MAX E), Minimum Error (MIN E) and Mean Absolute Percentage Error (MAPE).

Table 4 - Comparison of metrics between PL models and ANN

Study	Place	Frequencies (MHz)	Learning Algorithm	Performance Metrics
Ayadi, Ben Zineb, Tabbane (2017)	Tunis, Tunisia	450-850-1850-2100 and 2600	Gradient Descent	MAE, σ, R^2, MIN E, MAX E, ME, RMSE
Popoola, Faruk et al. (2019)	Ilorin, Nigeria	203.25	SCG and LM	ME, RMSE, sigma and R^2
Popescu, Nafomita, et al.(2001)	Kavala, Greece	1890	LM	ME, σ and R^2
Benmus, Abboud, Shatter (2015)	Tripoli, Libia	900-1800 and 2100	Not Informed	RMSE
Eichie, Oyedum, et al.(2017)	Niger State, Nigeria	1800	LM	RMSE
Cheerla, Ratnam, Borra (2018)	Vijayawad, India	800 and 1800	LM	MAE and MAPE
Ferreira, Matos, Silva (2016)	Rio de Janeiro, Brazil	1140	LM	sigma
Park, Tettey, Jo (2019)	Not Informed	3400-5300 and 6400	L-BFGS	RMSE
Sotiroudis, Siakavara (2015)	Not Informed	900	Ray Tracing	MAPE and RMSE

Source: The Authors (2022)

Table 5 comprises of the performance metrics presented both by the aforementioned studies and by this study. The ME, MAE, RMSE, σ and R^2 was chosen.

Table 5 - Comparison of metrics between PL models and ANN

Study	Frequencies (MHz)	ME	MAE	RMSE	σ	R^2
Ayadi, Ben Zineb, Tabbane (2017)	450	-0.94	-	-	6.21	0.878
	850	-0.74	-	-	6.43	0.791
	1850	0.38	-	-	6.08	0.810
	2100	0.62	-	-	6.87	0.894

	2600	0.50	-	-	6.53	0.852
Popoola, Faruk et al. (2019)	203.25	3,746	-	5,101	3,462	0,946
Popescu, Nafomita, et al.(2001)	1890	5,04	-	6,63	4,3	-
Benmus, Abboud, Shatter (2015)	900	-	-	4,35	-	-
	1800	-	-	5,314	-	-
	2100	-	-	3,353	-	-
Eichie, Oyedum, et al.(2017)	1800	-	-	1,22	-	-
Cheerla, Ratnam, Borra (2018)	800	-	0,41	-	0,21	-
	1800	-	0,46	-	0,43	-
Ferreira, Matos, Silva (2016)	1140	-	-	-	2,86	-
Park, Tettey, Jo (2019)	3400	-	-	7,812	-	-
	5300	-	-	7,185	-	-
	6400	-	-	8,034	-	-
Sotiroudis, Siakavara (2015)	900	-	2.74	3.54	-	-
This Work	569,143	-	2,23	2,879	1,82	0,936

Source: The Authors (2022)

CONCLUSION

The purpose of this article was to collect RSS data from UHF signals, in the frequency range of 566 to 572 MHz, TV Channel 30 in the city of Uberlândia (Brazil), and then compare the measured values with theoretical values obtained from propagation models in the literature and the model developed based on an ANN. From this comparison, the conclusion was reached that the ANN model presented the best result when compared to the theoretical models, as evidenced through the MSE (2.879) and σ (1.82). In addition, the ANN model validated the best regression performance as evidenced by the R^2 (0.936). Therefore, the ANN model generated can perform the prediction of the PL for broadcasting links.

In comparison with other studies, the model proposed in this study showed very similar results, in relation to the MAE. However, this study presented a better result than the study Sotiroudis, Siakavara (2015) and worse than Cheerla, Ratnam, Borra (2018), in relation to the RMSE. The study presented herein demonstrated better results than Popoola, Faruk, et al. (2019), Popescu, Nafomita, et al. (2001), Benmus, Abboud, Shatter (2015), Park, Tettey, Jo (2019) and Sotiroudis, Siakavara (2015), but was inferior when analysing the results obtained by Eichie, Oyedum, et al. (2017). In terms of the standard deviation, only study Cheerla, Ratnam, Borra (2018) obtained better results than those obtained in the presented study for this parameter. Regarding those studies that presented

R^2, this study obtained better result to all other studies but Popoola, Faruk, et al. (2019), which demonstrated a superior result. Each study was carried out in a different location, with different geographic characteristics, pre-processing, and equipment, among other parameters. Due to such, there is no way to state that one study was superior to the other just by analysing the statistical data.

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