# SIGNAL POWER LOSS PREDICTION USING ARTIFICIAL INTELLIGENCE

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**Abstract** In this study, we conducted a machine learning approach to propose a mobile telephony signal propagation model using regression. The acquisition of signal propagation models provides relevant indicators about the network signal quality offered to users. Although the most advanced technology is 5G, a study was developed using 3G and 4G data, since the implementation of 5G in Brazil is still a distant scenario. Signal power loss data from a single operator were collected through the G-Net Track application and processed using Haversine. This enabled the application of linear regression technique to obtain a model representing signal power loss. The regression-generated result was compared to nine literature models, including Rappaport, Okumura-Hata, ECC33, Modified Cost231-Hata, SUI, Extended SUI, Walfish-Ikegami, and Ericson999. The results from the sampled data indicate that the literature models do not adequately represent the signal behavior, and that the application of linear regression produces a solution capable of representing, in a more realistic manner, the behavior of 3G and 4G signal power loss concerning the transmitting antenna. Through this study, we aim to comprehend the heterogeneity of the network infrastructure and contribute by providing research that aids in the formulation of public policies to enhance the Brazilian telecommunications system.

**Keywords:** mobile signal propagation, machine learning, linear regression.

## 1 introduction

The digital information and communication technology is one of the main characteristics of the globalized world. It is perceived across various social spheres and is embedded in individuals' relationships and knowledge production. With the increasing access to information on mobile devices through mobile internet [1], mobile telephony has seen significant advancements in telecommunications infrastructure over the last few years. This evolution started in the 1950s with vacuum tube equipment and has progressed through LTE and the recent 5G technologies [2]. This progress has enabled a multitude of data-intensive applications to be viable, as network infrastructure continually adapts to meet the demands of data flow from these applications. This is reflected in network operability, optimization of machine-to-machine communication processes, and investments in Brazilian service provider backbones and central facilities.

However, in the Brazilian context, the improvement in telephony quality has been uneven, heterogeneous, and below that of other countries [3]. Mobile phone users frequently complain about connectivity issues they face [4]. This situation arises from the technical and operational factors required to ensure mobile terminal mobility [3, 5]. Factors of technological availability (market-available technology), socioeconomic conditions, and structural constraints hinder access to more advanced telecommunication technologies in Brazil. Factors like rural expansion, state incentives, and Human Development Index (HDI) measurements significantly influence service availability and quality. Furthermore, challenges in signal propagation, such as regional topography (terrain, mountains, etc.), channel interference, terminal identification, network terminal capacity, and variable densities of mobile terminals at different network points, contribute to the problem.

Thus, evaluating signal quality indicators is of utmost importance for measuring and ensuring the success of connections between fixed and mobile devices, thus guaranteeing access and regional development. One way to evaluate mobile telephony signal quality is through classical models available in the literature [6]. Telecommunication companies operate their services considering the signal as ideal in the design model. These models describe signal propagation and enable the extraction of network quality parameters [7]. However, due to the heterogeneity of the Brazilian telecommunications system, design models do not always adequately represent network standards for a given location. Inconsistencies between the model and reality can lead to telephony service overload and compromise user demand fulfillment. This affects various sectors reliant on telephony for operations, including critical services like hospitals, schools, and companies utilizing mobile services.

For tasks related to prediction and function approximation, artificial intelligence algorithms have been extensively explored in various knowledge areas due to their ability to accurately represent relationships between variables [8]. Among these algorithms, linear regression is known for yielding effective models from data [9, 10]. Therefore, this study aims to explore linear regression to obtain a model that can represent technical and operational factors present in real mobile network data. The objective is to provide a more realistic overview of mobile network behavior. This is expected to contribute to technical studies supporting the formulation of public policies aimed at enhancing user quality of life.

To achieve this, this study presents a case study on 4G signal power loss from a mobile network operator. While the latest mobile communication technology is 5G, it remains distant in the Brazilian context [3–5]. The findings of this study demonstrate that the behavior of the telephony network does not align with the models available in the literature. Additionally, they point to a slow progression towards 5G network implementation, as the existing infrastructure of 3G and 4G technologies, albeit simpler than 5G, exhibit high levels of signal power loss.

## 2 Methodology

In order to underpin the case study addressed in this work and illustrate the effectiveness of linear regression as a suitable solution for evaluating signal oscillation behavior in 3G and 4G transmissions, crucial steps were delineated in the methodological process. These encompassed antenna data research, data collection and processing, the implementation of a comparative process with the state of the art, and the definition, as well as discussions on the proposed machine learning model.

Regarding the research of antenna data, for the purpose of simplification, the decision was made to consider a single antenna as the source of the mobile transmission signal. Data related to this antenna were obtained from the Conexis Brasil Digital platform [11], a Brazilian entity that brings together the main telecommunications companies in the country.

Over a period of 20 days, from Monday to Friday, at a consistent time and following a similar route, data on signal power loss, measured in decibels (dB), were collected from a single telecom operator. This collection was carried out using the G-nettrack Lite application. The application, available for free on Android and Apple platforms, enabled the monitoring of 3G and 4G mobile networks without the need for specialized equipment. The G-Net Track Lite, after configuring the appropriate parameters, allowed the extraction of records in txt and kml file formats.

Once the data of interest was collected, it proceeded to organize this data, encompassing information such as latitude, longitude, and signal power loss. Initially, the composition generated by the application was stored in a txt file format. To facilitate analysis and enhance investigative breadth, this data was converted to the .csv format, becoming a valid input for the proposed model. Utilizing the distances obtained during collection, the Haversine formula was applied to calculate the distance between the point of signal loss and the selected antenna.

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

where:

- $\Delta\phi$ is the difference in latitude between the two points;
- $\Delta\lambda$ is the difference in longitude between the two points;
- $\phi_1$ and $\phi_2$ are the latitudes of the two points.

With the completion of data collection, necessary data transformations and adaptations, distances were calculated in relation to the antenna, along with the corresponding signal power loss, using the models from the literature. For this process, the following models were considered: Rappaport, Okumura-Hata, ECC33, Modified Cost231-Hata, SUI, Extended SUI, Walfish-Ikegami, and Ericson999.

Obtaining the machine learning model: the linear regression model was chosen as it is a simple model capable of effectively approximating functions [9, 10, 12]. The scikit-learn library was employed to create linear regression using signal power loss data relative to the distance from the signal transmission point (antenna).

For the environment setup of this work, the following were used:

- Hardware: Windows 11 Home x64, 16GB RAM and Intel(R) Core(TM) i7-10510U CPU @ 1.80GHz 2.30GHz.
- Programming language: Python 3.9.16.
- Web-based interactive computing platform: Project Jupyter.
- Main Python Libraries: TensorFlow 2.8.0, Keras 2.12.0, Pandas 1.4.1, NumPy 1.22.3, Matplotlib 3.5.1 and Scikit-learn 1.0.2.

## 3 Results and Discussions

The heat map depicted in Figure 1:

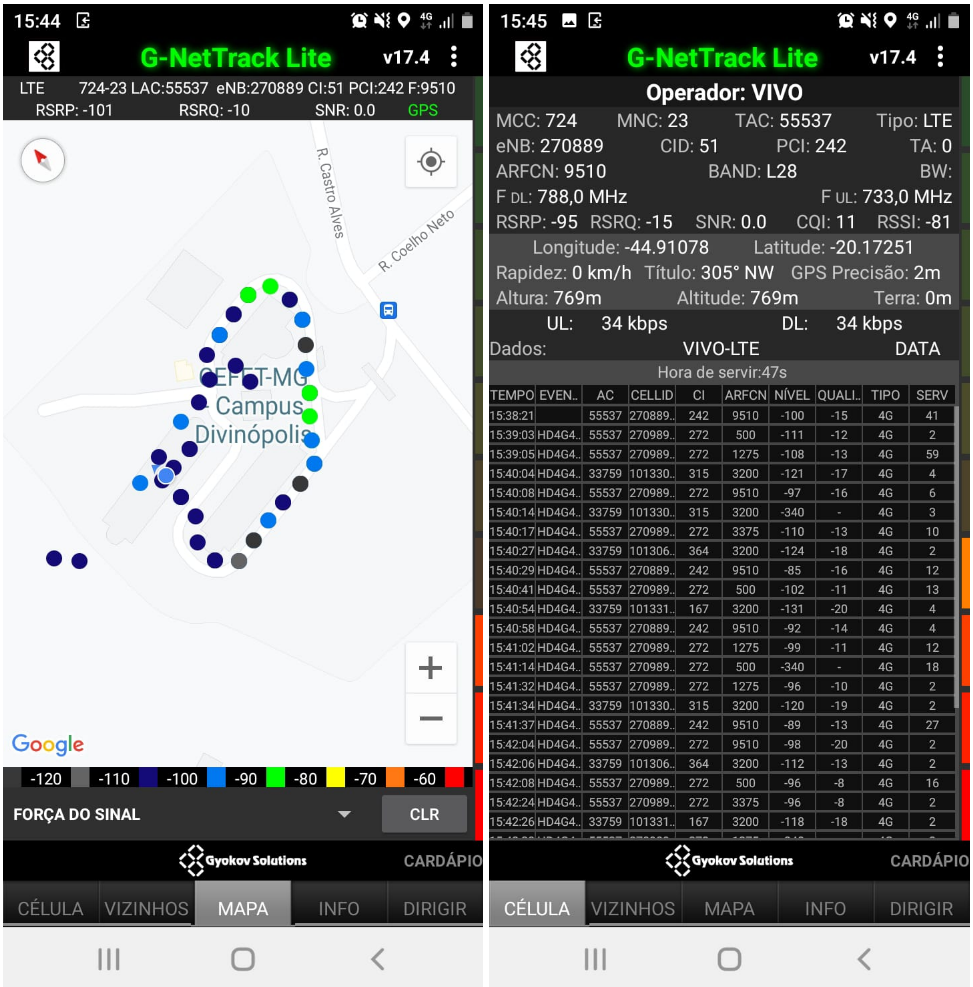


Figure 1. Heat map and sample of generated tables.

sketches the journey undertaken, meticulously recorded, and the real-time data collected by the G-Net Track Lite (free version) was visually represented with different colors. The application facilitated the continuous capture of instantaneous position and velocity through the cellphone's GPS. The prevalence of gray points, indicating high signal power loss, underscores the correlation between this characteristic and lower signal quality, resulting in a more compromised transmission experience.

In the development of the model, we used the data on distance relative to the antenna, the source point of signal transmission, along with the corresponding signal power loss. To achieve a comprehensive analysis, all models were unified in a single analysis to clearly visualize the behavior of each model in relation to the research data. For this purpose, specific colors were assigned to each model, as shown in Figure 3.

Exploring the correlation among the examined data, we constructed a graph encapsulating the outcome of our investigations. In this visual representation, we compared the ideal free space model with various formulations of signal power loss identified in the literature, as illustrated in Figure 3.

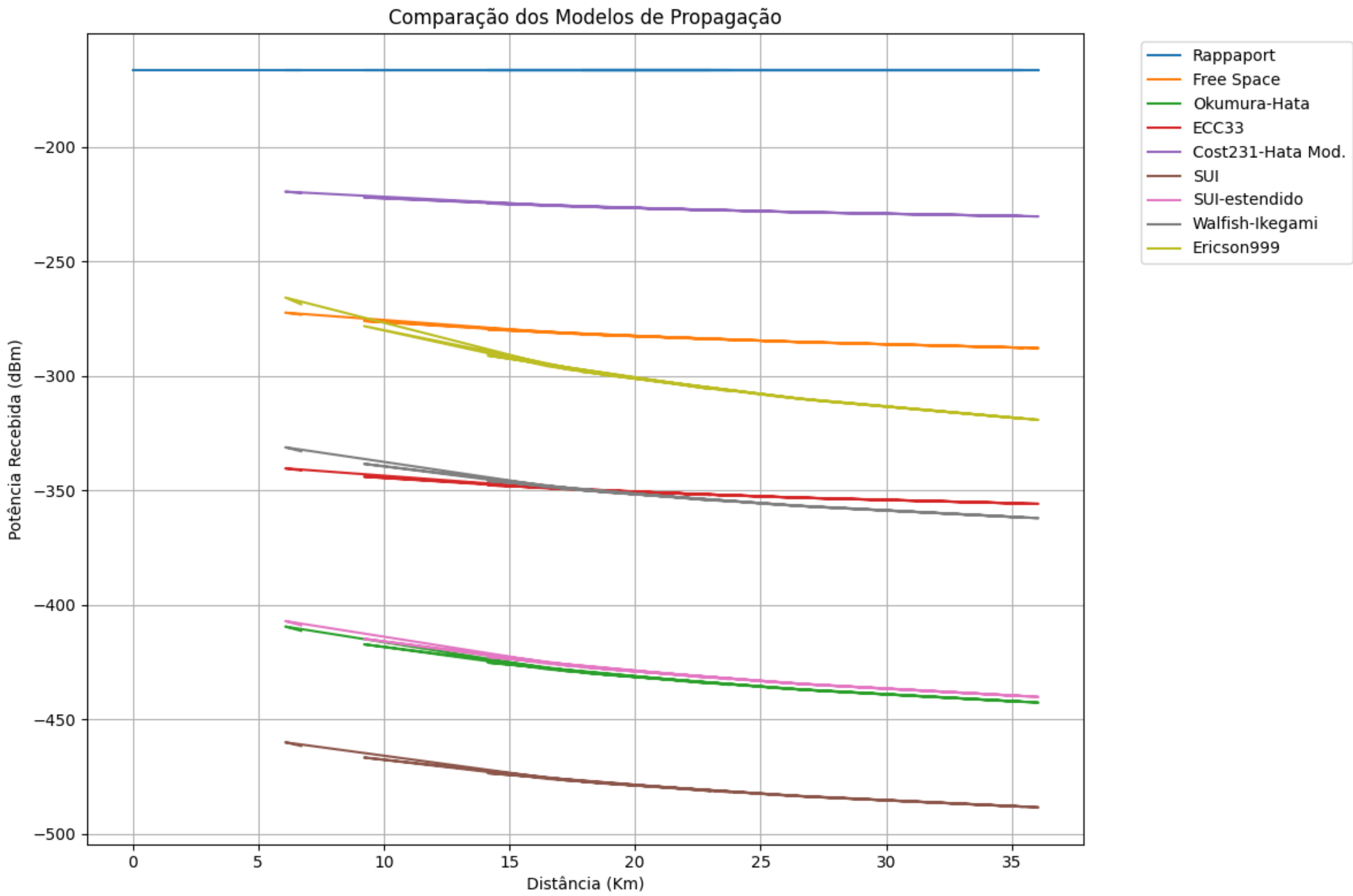


Figure 2. Comparison of signal power loss among literature models

Notably, we observed that the free space test model, despite its prominence, does not align with any of the traditional models discussed in the literature. This disparity points to a notable lack of coherence concerning the stability normally expected.

This observation stands out as an intriguing finding, as the free space test model is often adopted as a benchmark for stable and predictable behavior. The evident divergence from conventional models raises questions about the specifics of the testing environment used or even the possible influence of unaccounted variables that might be impacting the transmission system's behavior.

This result prompts us to delve deeper into the factors that may contribute to this discrepancy, from specific characteristics of the study region to potential external interferences. Furthermore, this finding emphasizes the need to develop more adapted and customized approaches to assess signal propagation in this unique context, in order to gain a more accurate and comprehensive understanding of the communication system's behavior.

## 4 Conclusion

After conducting detailed and comprehensive analyses, we were able to identify, through a meticulous examination of the graphs, that the reduction in signal intensity in the investigated area, encompassing the city of Divinópolis, exhibits a pattern of variation that departs from the parameters established by traditional models of signal propagation, recognized for their reliability and predictability. The graphs revealed a complex series of signal power fluctuations, whose behavior does not align adequately with conventional propagation equations. The measurements highlight a notable incongruence in intensity levels relative to the distance between the transmitting and receiving stations, deviating significantly from values projected by standardized models.

The observed instability in signal power loss can lead to connectivity issues, resulting in low-quality transmissions and service disruptions, compromising the user experience and limiting the potential of applications and services. Additionally, this situation may pose supplementary challenges in implementing innovative technologies such as the Internet of Things (IoT) and Vehicle-to-Everything (V2X) communication, both of which rely on a stable and reliable network infrastructure. Given this complexity, a deeper investigation into the specific variables influencing signal behavior becomes imperative in order to develop tailored solutions that ensure connectivity stability and enable the full utilization of available technological capabilities for advancing the region.

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