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RESEARCH ARTICLEOPEN ACCESS

ANALYSIS OF LORA SIGNAL PROPAGATION IN URBAN ENVIRONMENT

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ABSTRACT

This paper analyzes LoRa signal propagation in an urban environment, based on RSSI collections conducted at various distances ranging from 10 to 1610 meters. The data were analyzed using the log-normal shadowing model, allowing the generation of path loss graphs. The coefficient of determination (R^2) for the log-normal model was 0.9764, with an RMSE of 3.2872 and an MAE of 2.4020, indicating an excellent fit to the data. As a comparison between regression methods, the quadratic approximation presented an R^2 of 0.9117, RMSE of 6.1397, and MAE of 5.2137, reflecting lower performance. These results highlight the impact of distance on signal attenuation and confirm the effectiveness of the log-normal shadowing model in representing propagation in urban scenarios. The research contributes to understanding LoRa performance in dense environments, providing valuable insights for the planning and optimization of LoRa networks, as well as serving as a practical guide for future applications in the Internet of Things context.

I. INTRODUCTION

LoRa® technology (Long Range) has become one of the main solutions for IoT (Internet of Things) networks, offering long-distance communication with low energy consumption [1], [2]. Its applications span areas such as smart cities (as shown in Figure 1), precision agriculture, and environmental monitoring. This paper investigates the performance of the LoRa signal in an urban environment, focusing on signal propagation at various distances. The research validates the results using the log-normal shadowing and quadratic approximation models, contributing to the development of more accurate propagation models and the optimization of LoRa networks in dense urban scenarios.

The propagation analysis is essential to optimize LoRa technology in urban environments, ensuring the efficiency and reliability of data transmissions in projects proposed in the literature, despite the presence of obstacles.

The study in [3] proposes a Vehicle Monitoring System (VMS) based on IoT to collect environmental and vehicle performance data in urban areas. The system uses sensors to monitor parameters such as air quality (PM2.5, NO2, CO, O3), temperature, and humidity, as well as vehicle information via OBD-II and GPS location. The data is transmitted to a cloud server via LoRa technology. The system provides a graphical interface for real-time data visualization, which can be used by both drivers and government authorities for traffic planning and environmental decision-making. Expanding the LoRa gateway infrastructure in the city could enhance transmission stability and contribute to the development of smart cities.

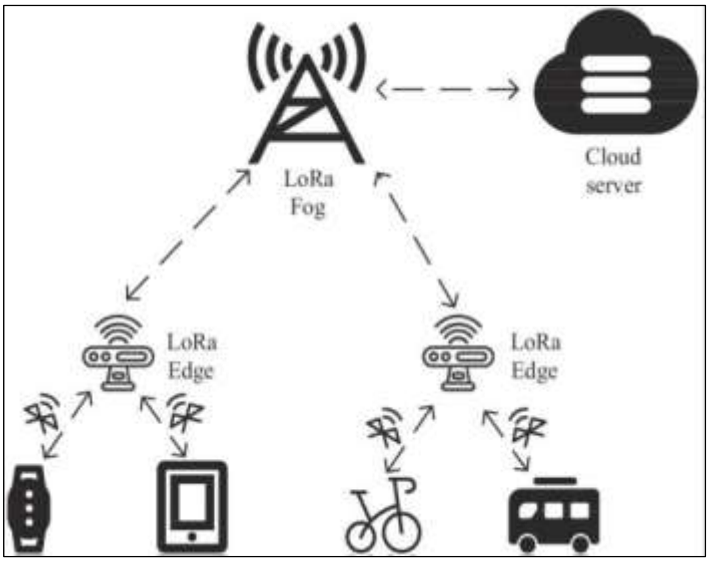

Figure 1: A hybrid LoRa and Bluetooth city network.
Source:[1].

The article [4] presents a collaborative sensor network based on LoRa for pollution monitoring in smart cities. The system uses geo-located nodes to measure temperature, relative humidity, and CO2 concentration, while also considering citizens' opinions. Using the collected data and city policies, the system controls traffic flow and advises citizens to avoid polluted areas. Tested in a real environment, the low-cost system proved effective in detecting CO2 levels. Future work aims to expand the application to larger areas and include additional parameters such as CO and vehicle volume.

The work done in [5] proposes a Fleet Management and Tracking System using LoRa, a low-power, long-range solution for monitoring and managing vehicle fleets. Each vehicle is equipped with a transmitter that includes an Arduino Nano, GPS module, switch, buzzer, and LoRa module. The GPS provides real-time location data, which is sent to the receiver unit at the management center via LoRa, where it is displayed on an LCD screen. The system also allows for emergency alerts and audible notifications in case of unauthorized movements or route deviations, enhancing security. It is scalable, easy to integrate with additional vehicles, and suitable for remote areas where traditional cellular networks are limited. This system offers a reliable and cost-effective alternative to traditional tracking, improving safety and operational efficiency, especially in challenging and remote locations.

In the present work, RSSI (Received Signal Strength Indicator) data collection was conducted practically at distances ranging from 10 to 1610 meters, covering different propagation conditions. The comparative analysis between the log-normal shadowing and quadratic approximation models allowed for a better understanding of signal attenuation and the challenges posed by urban obstacles such as buildings and interference.

Unlike other studies focused on rural environments [6] or line-of-sight scenarios, this paper focuses on the particularities of an urban environment, providing valuable insights for planning LoRa networks in areas with high construction density. The results obtained can be applied to improve coverage and efficiency of IoT networks, which is essential for future implementations in smart cities and other urban contexts.

This article is organized into the following sections: Section II presents the relevant concepts for conducting the studies. Section III presents the materials and methods addressed in this study. Section IV outlines the results obtained, and Section V presents the conclusion of the research.

II. THEORETICAL REFERENCE

II.1 LONG RANGE

LoRa (Long Range) is a wireless communication technology designed to transmit data over long distances with low power consumption. Based on Chirp Spread Spectrum (CSS) modulation, it offers high reception sensitivity, making it ideal for sensor networks and Internet of Things (IoT) applications. Operating in unlicensed frequency bands such as ISM (Industrial, Scientific, and Medical), it uses specific bands that vary by region: 433 MHz, 868 MHz (Europe), and 915 MHz (Americas) [7].

This operational flexibility allows LoRa to be applied in both urban and rural environments, even in locations with physical barriers or large distances. LoRa can reach distances of up to 15 km in rural areas and 2 to 5 km in urban environments, depending on the conditions [8]. Additionally, LoRa offers a relatively low data transmission rate but is sufficient for many IoT applications, ranging from 0.3 kbps to 27 kbps. This ensures efficient communication on a large scale, even in challenging network conditions.

LoRa is an integral part of LoRaWAN networks, which offer advanced security features, device management, and support for thousands of connected devices. LoRaWAN networks are highly scalable, making them suitable for projects involving large numbers of connected devices without overloading the network infrastructure. The CSS modulation used by LoRa also provides greater resilience to interference, ensuring communication in crowded environments or areas with many interference sources.

The technology is widely used in areas such as smart agriculture, smart cities, remote metering, and logistics tracking, standing out for its combination of range, energy efficiency, robustness, and compatibility with different frequency regulations worldwide.

II.2 LOG-NORMAL SHADOWING

The log-normal shadowing model is widely used to analyze the impact of obstacles on the propagation of radiofrequency signals [9]. This model is described by the equation:

$$PL(d) = PL(d_0) + 10\, n \log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad (1)$$

where $PL(d)$ is the path loss at a distance d, $PL(d_0)$ is the reference path loss at a distance d_0, n is the path loss exponent, and X_σ is the normal deviation component (shadowing variability).

According to the model, after determining the values of n and σ, the received power at distances not included during the collection can be estimated using the following equation [10]:

$$P_r(d) = P_r(d_0) - 10n \log_{10}\left(\frac{d}{d_0}\right) \qquad (2)$$

where $P_r(d) + X_\sigma$ is the estimated received power at the distance of interest d, and $P_r(d_0)$ is the received power at the reference distance d_0.

II.3 QUADRATIC APPROXIMATION

The quadratic approximation is capable of establishing a function using only a few points from a curve. Therefore, it can be used to estimate parameters of a semi-deterministic model and/or predict values for that model [11]. In other words, it can be used to create an equation that describes a curve between five points from a reading (e.g., RSSI), allowing the estimation of RSSI for any distance.

The quadratic approximation is easily applied in experiments that use RSSI, which decreases exponentially with the increase in distance, exhibiting second-order behavior. In this context, the number of observed points n can be greater than the degree of the polynomial g [11].

$$U_g(x) = b_0 + b_1 x + b_2 x^2 + \cdots + b_g x^g \qquad (3)$$

since $g < n - 1$.

The equations can be appropriately described in matrix form, as in the system below:

$$X^T X a = X^T f \tag{4}$$

where

$$X = \begin{pmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{pmatrix},$$

X^T is the transpose of the matrix X, which, for example, contains the distance values related to their respective RSSI

values present in the matrix $f = \begin{pmatrix} f_1 \\ \vdots \\ f_n \end{pmatrix}$. The matrix $a = \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_m \end{pmatrix}$

represents the coefficients of the quadratic approximation polynomial that is to be determined. The equations of this system are referred to as normal equations. This nomenclature arises because the system can be written as:

$$X^T (Xa - f) = 0 \tag{5}$$

The components of the vector $(Xa - f)$ are given by the residuals of the approximation, and according to the previous equation, this vector is orthogonal to the vectors formed by the elements of the rows of the matrix X^T, which are in the form

$$\begin{pmatrix} x_1^l \\ x_2^l \\ \vdots \\ x_n^l \end{pmatrix} \text{ with } l = 0, 1, 2, \ldots, m.$$

III. MATERIALS AND METHODS

The tests were conducted using a Kerlink indoor LoRaWAN Gateway [12], positioned at a height of 7 meters, while the transmitter (LoRa® module) [13], powered by 3.6V derived from a 12V and 1.2Ah battery, was transported by car, starting 10 meters from the Gateway.

The Kerlink LoRaWAN indoor gateway, illustrated in Figure 2, connects LoRa sensors to cloud servers, enabling indoor IoT networks with Ethernet, Wi-Fi, or cellular connectivity, and is used in applications such as smart cities and automation. The LoRa® module, illustrated in Figure 3, is a low-power wireless technology for long-distance point-to-point communication. Widely used in IoT networks, it enables smart applications like energy management, natural resource control, environmental monitoring, and disaster prevention, operating via AT commands through the serial port (9600 bps).

To better model the collected data, a performance comparison was made between the log-normal shadowing model [10, 14] and quadratic fitting [15], using the metrics coefficient of determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) [16]. The coefficient of determination R^2 evaluates the proportion of data variance explained by the model, ranging from 0 to 1, with higher values indicating better fit, as shown in equation 6.

Figure 2: Gateway LoRaWAN indoor.
Source: Kerlink, (2024).

Figure 3: Módulo LoRa®.
Source: Iot-Labs, (2024).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{6}$$

where y_i are the observed real values, $\hat{y}_i$ are the values estimated by the regression model, $\bar{y}$ is the mean of the real values, and n is the total number of observations.

RMSE measures the average error between observed and predicted values, penalizing larger deviations more heavily, as shown in equation 7.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{7}$$

where y_i are the observed real values, $\hat{y}_i$ are the values predicted by the regression model, and n is the total number of observations.

MAE calculates the mean of the absolute errors, being less influenced by outliers compared to other metrics like RMSE. The formula for MAE is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (8)$$

where y_i are the observed real values, $\hat{y}_i$ are the values predicted by the model, and n is the total number of observations.

These metrics were employed complementarily, allowing for a detailed analysis of the fit quality and error magnitude, contributing to the evaluation of model performance under different conditions.

IV. RESULTS

To analyze the propagation of the LoRa signal, the log-normal shadowing model was applied to the collected data. Table 1 summarizes the collected data, presenting the distance (in meters) and the corresponding RSSI (in dBm).

Table 1: Data collected.

Distance (m)	RSSI (dBm)
10	-65
110	-86
310	-108
510	-112
1010	-121
1610	-123

Source: Authors, (2025).

From approximately 2 km onward, no packets were received, highlighting the limitations of the indoor Gateway in urban environments.

The log-normal shadowing model is a widely used statistical model to describe signal attenuation in urban environments. It accounts for random variations caused by obstructions and the dispersion of the signal around an average value. In the log-normal propagation model, the path loss (PL) can be expressed by the equation 1.

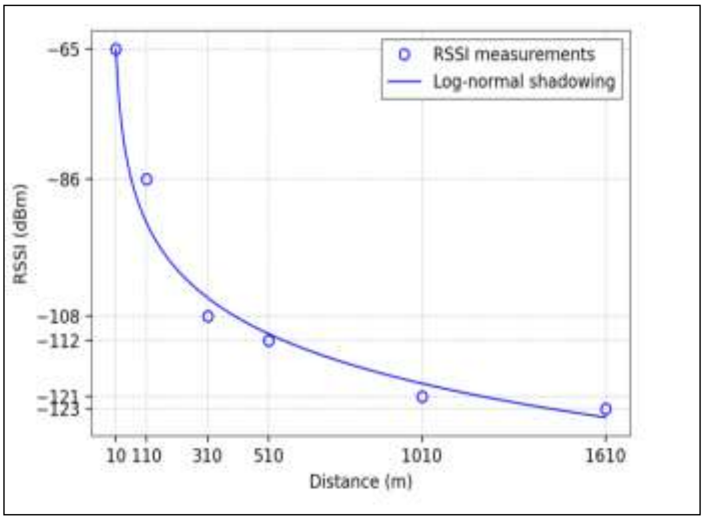

Figure 4: RSSI as a function of distance.
Source: Authors, (2025).

In short distances between 10 and 110 meters, the initial RSSI of -65 dBm gradually decreased, reaching -86 dBm at 110 meters, as shown in Figure 4. This loss suggests that, even at short distances, the urban environment impacts signal propagation due to the presence of obstacles and interference. At longer distances between 310 and 1610 meters, the signal loss became more pronounced, ranging from -108 dBm to -123 dBm.

The observed behavior reflects the additional challenges imposed by urban obstacles such as buildings, vegetation, and constructions, which intensify signal fading. For the log-normal shadowing model, the coefficient of determination (R^2) was 0.9764, the RMSE was 3.2872, and the MAE was 2.4020.

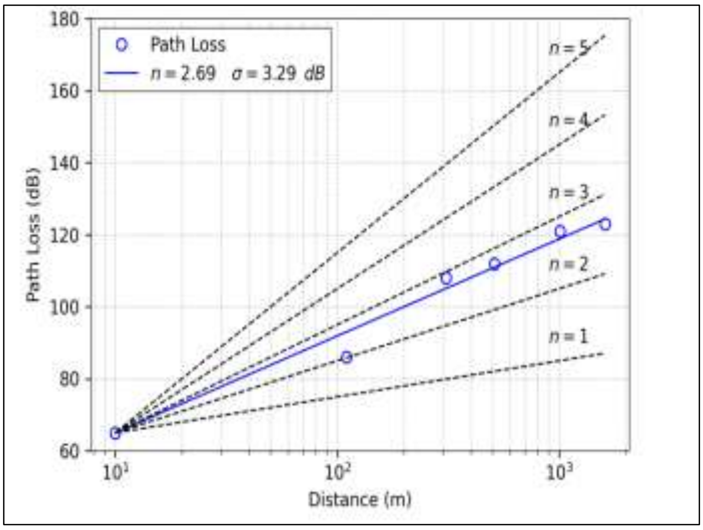

Figure 5: Path Loss as a function of distance.
Source: Authors, (2025).

Path loss (PL) was calculated for distances from 10 meters to 1610 meters, as shown in Figure 5. The propagation model applied in the urban test resulted in a path loss exponent (n) value of 2.69 and a standard deviation (σ) of $\sigma = 3.29$ dB. These values indicate signal attenuation and path loss variability in the studied urban scenario, contributing to the understanding of LoRa signal behavior at different distances and conditions.

Additionally, a quadratic curve fitting was applied to the collected RSSI data. The fitted curve can be observed in Figure 6.

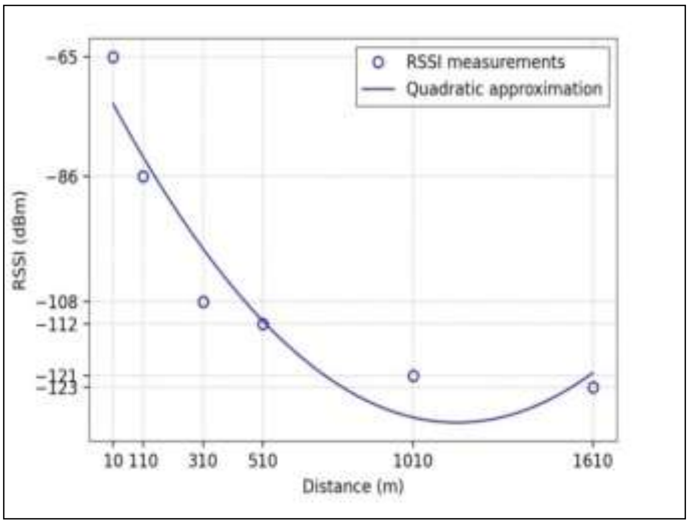

Figure 6: Quadratic approximation of measurements.
Source: Authors, (2025).

The fitting resulted in the equation 9.

$$y = 0.0000425669261x^2 - 0.0984761724x - 72.3111221 \quad (9)$$

The coefficient of determination (R^2) for the quadratic approximation was 0.9117, the RMSE was 6.1397, and the MAE was 5.2137, indicating that the quadratic model fits the collected data well, reflecting the behavior of the signal as a function of distance. For example, path loss increased significantly as the distance grew, demonstrating the communication challenges in dense urban areas.

Table 2 presents the statistics of the metrics evaluated for the two models compared.

Table 2: Metrics.

Model	R^2	RMSE	MAE
Log-normal Shadowing	0.9764	3.2872	2.4020
Quadratic Approximation	0.9117	6.1397	5.2137

Source: Authors, (2025).

The analysis revealed that signal attenuation followed the expected behavior, with a marked decrease as the distance increased. Obstacles such as buildings and vegetation areas generated variability in the RSSI behavior, characterizing the urban environment as challenging for LoRa communication.

By using an outdoor LoRaWAN Gateway, designed for external environments, better performance is expected, including greater range and better packet reception rate. This upgrade should mitigate the limitations identified in this study.

The log-normal shadowing model outperformed the quadratic approximation. It obtained a higher coefficient of determination (R^2), indicating a greater ability to explain the variance of the data. Additionally, it had a lower RMSE, reflecting a smaller influence of outliers, and a lower MAE, showing reduced mean absolute errors. These results reinforce the higher precision and suitability of the log-normal shadowing model.

V. CONCLUSIONS

Based on the obtained results, the log-normal shadowing model demonstrated significantly better performance compared to the quadratic approximation. The coefficient of determination (R^2) of the log-normal shadowing model was 0.9764, indicating a greater ability to explain the variance of the data compared to the R^2 of the quadratic approximation, which was 0.9117.

Additionally, the log-normal shadowing model showed lower values of RMSE (3.2872) and MAE (2.4020), reflecting lower average errors and less influence from outliers. In contrast, the quadratic approximation had an RMSE of 6.1397 and an MAE of 5.2137, indicating a less precise fit. Therefore, it can be concluded that the log-normal shadowing model is more effective and reliable for representing the signal propagation data analyzed, proving to be a superior choice compared to the quadratic approximation.

The analysis highlights that LoRa communication is viable in urban scenarios, but the signal quality is significantly affected by distance and the presence of physical obstacles. The implementation of equipment optimized for outdoor use and strategies to mitigate urban effects will be essential to improve performance and extend the range of LoRa communication in dense environments.

In future work, it is proposed to evaluate the propagation of the LoRa signal in multiple urban locations across the city, aiming to assess the overall path loss. Additionally, the delay spread will be analyzed to better understand the multipath effects of the propagated signal.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: David Alan de Oliveira Ferreira.
Methodology: David Alan de Oliveira Ferreira.
Investigation: David Alan de Oliveira Ferreira.
Discussion of results: David Alan de Oliveira Ferreira.
Writing – Original Draft: David Alan de Oliveira Ferreira.
Writing – Review and Editing: David Alan de Oliveira Ferreira.
Supervision: David Alan de Oliveira Ferreira.
Approval of the final text: David Alan de Oliveira Ferreira.

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