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Machine Learning-Based Analysis of Packet Delivery Rate in LoRaWAN in Tropical Urban Environments: Case Study of Benin City, Edo State, Nigeria

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Abstract

Low Power Wide Area (LPWA) communication protocols are essential for IoT due to their low power consumption and extensive communication range. LoRa technology, a key LPWA protocol, has garnered significant interest for its long-range, low-power wireless communication capabilities under the LoRaWAN standard, making it ideal for networks requiring long distances and prolonged battery life. However, few, if any, empirical studies involving the packet delivery ratio (PDR) performance of LoRaWAN networks have been carried out in the specific study location using both Machine learning and Deep learning. In our paper, the PDR performance of LoRaWAN networks in an urban tropical region, specifically Benin City, Edo State, Nigeria, was assessed using a Dragino LG02 dual-channel kit gateway with two SX1276/SX1278 radio chips, during the dry season. Experiments measured parameters such as distance, RSSI, altitude, and packet transmission data to derive PDR. Machine learning and deep learning models such as Multiple Linear Regression (MLR), Support Vector Regression (SVR), Random Forest (RF) and Artificial Neural Networks (ANN) were used to predict PDR in the test environment. It was experimented with the MLR and the ANN model that was showing the best performance after evaluation of the test set with the Root Mean Square Error (RMSE) metric, achieving error rates of 5.942 and 7.820, respectively. The path loss exponent was determined to be 3.048 for the test environment. The findings indicate successful deployment of LoRaWAN in the area, establishing key RSSI parameters and highlight that some machine learning models can serve as good predictive models for packet success rates.

Keywords: LoRaWAN, Benin City, Nigeria, PDR, Machine learning, Pathloss exponent, Tropical region

I. INTRODUCTION

Many industries are adopting Internet of Things (IoT) solutions, which typically consist of nodes with embedded microcontrollers that manage actions and communicate data with a gateway [1]. The gateway connects nodes in a local network using various protocols and links to a server via Ethernet to store data or receive commands. IoT applications are rapidly expanding across fields such as industry, farming, and home automation. Among the LPWAN protocols, LoRaWAN

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stands out for its use of unlicensed spectrum, its large communication range, and low power consumption [2].

Thus, it overcomes the challenges of long-range IoT communication, especially in areas without a functioning Internet. Studies have also shown that LoRaWAN can achieve up to 90.23% reliability in densely populated urban settings with proper configurations [3].

LoRaWAN, although a viable infrastructure, lacks much empirical information, especially in tropical areas like the area under test, i.e., Benin City, Nigeria. Its reliability in terms of packet delivery success rate in such terrains and the roles machine learning models can play in its prediction have not been extensively studied. This justifies that this research is worth doing for the new knowledge contribution to the LoRa WAN.

II. LITERATURE REVIEW

Chapungo and O. Postolach [4] evaluated the connectivity reliability of a LoRaWAN deployed in a rural area of Mozambique. Results indicate that both distance and terrain elevation significantly impact performance, with lower altitudes near end nodes resulting in degraded metrics. Despite operational challenges such as manual firmware resets and the absence of real-time monitoring, the network maintained a Packet Delivery Ratio (PDR) above 89% and operated autonomously for over 24 hours. The study underscores the advantage of placing gateways on natural elevations for enhanced coverage.

Abdullah et al. [5] examined the use of LoRaWAN networks to improve connectivity for IoT applications in Malaysian Oil Palm plantations by creating a machine learning-based signal attenuation model at 923 MHz LoRa setting. The model outperforms existing empirical models, offering better predictions for network planning and optimization.

A study by Saban et. al [6] carried out a LoRa star topology for long-range communication in indoor vs outdoor environments. Testing shows performance differences for LoRa in indoor versus outdoor environments, with gateway elevation identified as crucial for maximizing communication range by enhancing signal quality and achieving a Line of Sight (LoS). The work was carried out in Valencia, Spain.

Another study of Wu et.al [7] introduced a hybrid MAC protocol for LoRa aimed at improving upon the standard Pure ALOHA system, which suffers from high collision rates amid increasing IoT device traffic. The proposed solution integrates Distributed Queueing (DQ) to systematically arrange devices into logical queues, minimizing collision occurrences, and In-Band Full-Duplex (IBFD), enabling concurrent transmission of control signals and data by the Gateway. This optimization of LoRa parameters resulted in a notable 1.83x increase in throughput compared to existing methods.

This, being a mathematical model, would not be very practical in real-world environments with high noise or reflection that could drop performance significantly. Most reviewed literature does not evaluate or explore PDR as a function of RSSI, altitude and distance together. In addition, to the best of our knowledge and thorough examination of literature, this specific empirical methodology has not been applied to this study location, which is the urban area of Benin City, Edo State, Nigeria.

III. MATERIAL AND METHODS

A. *Experimental Setup*

The measuring system was composed of a receiver node consisting of an Arduino Uno + LoRa Shield + a 2.5dBi antenna, powered by a power bank.

The transmitter consisted of an Arduino Uno + LoRa Module and a Gateway, connected to The Things Network (TTN).

The LoRaWAN gateway used was the LG02 kit with two SX1276/SX1278 radio chips. It was selected for its affordability and its ability to act as a bridge to extend the range of the LoRaWAN signal from a remote sensor to a main gateway. It also has great compatibility with LPWAN protocols. The configurations used in this study are shown in Table I.

TABLE I. TECHNICAL SPECIFICATIONS OF THE END NODES

Parameters	Values
Spreading Factor (SF)	7
Bandwidth (BW)	125-500kHz
Coding Rate (CR)	4/5
Frequency Band	868MHz

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B. Experimental Procedure and Data Collection

This research was conducted in the urban center of Benin City, Edo, Nigeria. Benin City is located in Nigeria, West Africa, in the tropical rainforest belt. Annual average daily daytime temperatures range from 25-32 °C (77-90 °F) [8]. The region consists of two seasons, Dry and Rainy, with mean annual rainfall for the region given as ~2,284 mm or 90 inches per year, and a mean overall annual average relative humidity of 87% [9]. The measurements for this work were conducted during the dry season.

Twelve measurement points (1-13) were selected along ~4 km, with altitude differences up to 30 m. The gateway Geolocation of points is given below:

Latitude	**Longitude**
Point 1: 6.3191188	5.6239576
Point 2: 6.3156446	5.6269496
Point 3: 6.331110907	5.626949
Point 4: 6.310012	5.627954
Point 5: 6.3018712	5.6302415
Point 6: 6.3191188	5.6239576
Point 7: 6.3156446	5.6269496
Point 8: 6.331110907	5.626949
Point 9: 6.310012	5.627954
Point 10: 6.3018712	5.6302415
Point 11: 6.298456	5.630897
Point 12: 6.292195	5.6317872

C. Workflow of Experimental Design

The data collection process followed a structured sequence to evaluate connectivity at each designated test point.

Hardware Setup: The terminal node was configured using an Arduino Uno integrated with a Dragino LoRa Shield.

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The highest building elevation, also considered as Height Above Sea Level (HASL) was set to 10m for the transmitter module as it was placed on a two-storey building.

The receiver was hand-held and a manual walk-through and drive-through was done within the city around the selected test points. and the HASL was also measured for the receiver.

Packet Triggering: At each selected test point, the node was manually restarted to initiate the transmission of packets per cycle.

Repetition: This manual process was repeated per location for all twelve locations.

Analysis: Transmitted data was subsequently retrieved from The Things Network (TTN) console for performance evaluation.

Due to the specific environmental and operational conditions of the study, the following parameters were used:

i. ***Network Limitations:*** Due to sufficient Internet connectivity, real-time monitoring of data received was analyzed via the TTN console.
ii. ***Transmission Limits:*** To comply with 868 MHz duty-cycle regulations and manage limited power resources, a maximum of 12 packets was sent from each point.
iii. ***Data Minimization:*** Payloads were kept to a minimum to reduce the device's Time-on-Air (ToA) and conserve battery life.

D. Evaluated Metrics and Study Area

The primary performance indicator of interest was PDR (Packet Delivery Ratio).

A satellite view of the test area is shown in Fig. 1 (Google Maps),

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Fig. 1: Google Map View of the region of measurement within Benin City

E. Data Presentation and Tools

Data was collected into Tables in Microsoft Excel, while R and Python libraries were used to determine correlation coefficients and develop Machine Learning models for LoRaWAN propagation in the selected environments, specifically Multiple Linear Regression, Support Vector, and Random Forest. A deep learning model, consisting of an artificial neural network, was also developed from the data.

The reason for this was twofold: 1) it was done to compare the efficacy of different machine learning and deep learning predictive models for predicting LoRaWAN signal propagation. 2) it was done to determine the efficacy of these models; the Root Mean Square Error (RMSE) was used for evaluation.

F. Limitations of Experimental Design

Use of a single end node and Non-Line-of-Sight (nLOS) and Line-of-Sight (LOS) measurements are the limitations.

IV. RESULTS

Results established the direct influence of distance and altitude differences on LoRaWAN signal quality. The main measurement parameters are as shown in Table II.

TABLE II. INDICATORS PER MEASUREMENT POINT

X (Latitude)
Y (Longitude)
HASL
BW (KHz)
Tx(Km)
Avg.RSSI
Avg.SNR
CR
SF
Avg.B(bps)
Pkts. Sent
Pkts Rcvd
PDR
PTX
PathLoss

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The subsections below show detailed analyses for metrics such as RSSI and PDR and their graphical representations.

A. RSSI

RSSI showed a consistent decrease with increasing distance and decreasing altitude.

From about 500 meters from the transmitter, the RSSI was -110dBm for Bandwidth setting of 125kHz -115dBm for 250kHz and -116dBm for 500kHz settings. For comparison at 2km, RSSI values obtained were -117dB, -117dBm, and -116dBm for 125kHz, 250kHz and 500kHz settings, respectively.

Fig. 2 presents RSSI decline across multiple test points, showing attenuation due to distance and partial obstructions in line-of-sight conditions.

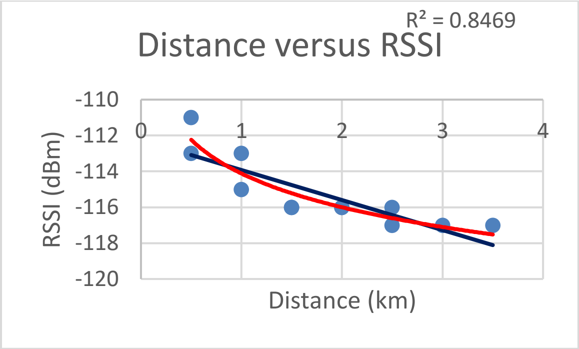

Fig. 2. RSSI per measurement point.

The blue trendline represents a linear relationship between distance and RSSI and obeys the theoretical inverse relationship and downward trend.

The red trend line represents an inverse exponential (logarithmic) relationship between RSSI and distance, which is consistent across other literature.

B. PDR

PDR, a derived metric from packets received and packets sent, had values that also showed a decrease with increased distance. At around 500 meters, a100% PDR was obtained across all bandwidths and at extreme distances of 2.5 km, PDR in some cases fell to about 61%.

Fig. 3 shows PDR as a function of distance.

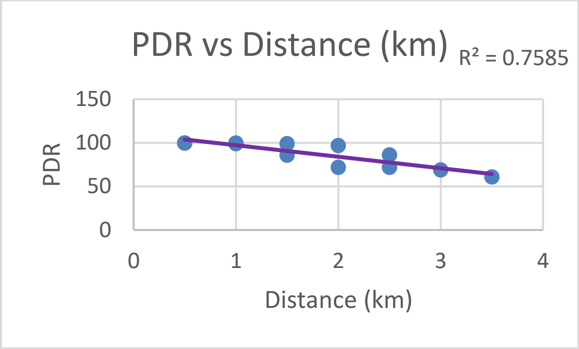

Fig. 3. PDR variation as a function of distance.

C. Machine Learning Models

Three machine learning models and one deep learning model were used to model packet success behaviour in the test environment. These models capture PDR as a function of altitude, RSSI, and increasing distance and can thus be used in packet delivery inferential purposes. The efficacy of these four (4) models was evaluated against each other using the Root Mean Square (RMSE) metric. This was done to ensure the fairness of the assessment using a single metric across all models.

The three machine learning models were developed using the R programming language. The dataset collected was fed into a variable for each algorithm and preprocessed.

The data was then split into 80% training and 20% testing subdata. An 80/20 split for the machine learning models ensured a final, unbiased performance estimate. A larger training set, about 90%, improves the learning of complex patterns but risks biased performance estimates due to less testing data. Conversely, a smaller training set of about 60% may lead to underfitting. The selected ratio indicates a trade-off that mitigates this. Keeping 20% of the data ensured the model was evaluated on unseen data, in order to assess real-world performance. The various machine learning algorithms were fitted to the training subdata, and the test data was used to evaluate the trained model with RMSE as the metric. The results from the various machine learning models are presented in Table III.

Table III

RMSE values for machine learning models.

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Machine Learning Model	RMSE Value
Multiple Linear Regression Model	5.942
Support Vector Regression Model	15.038
Random Forest Root Mean Squared Error	10.638
Deep Learning Model	7.8197

For the deep learning model, an artificial neural network consisting of two (2) hidden layers and one output layer was developed.

The dataset was divided into train, test, and validation sets of 70%, 20% and 10%. 70/20/10 was used to allow early stopping and hyperparameter selection on a validation set, thereby preserving the test set solely for final evaluation. The size of the validation set affects how sensitively overfitting can be detected. This architecture was fitted to the train set and evaluated using the test set and validated using the validation set. The RMSE was used as the evaluation metric in a similar fashion to the other machine models, and the results can be found in Table III. However, after trying out hyperparameter tuning, e.g. learning rate, there was no significant reduction in RMSE, as regards the deep learning model. Thus, it can be observed that the best performing model is the multiple linear regression model, followed by the deep learning model as shown in Table II. This shows that they are strong candidates for the prediction of LoRaWAN PDR for the test region and possibly other similar regions.

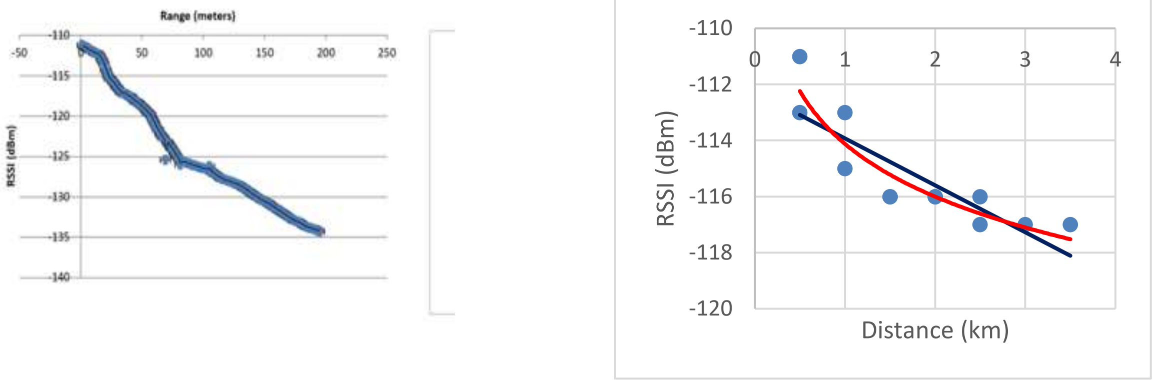

Fig. 4: RSSI models side by side

Comparison of the experimental RSSI model developed with previous works shows a strong correlation. This is illustrated in Fig. 4, which shows a side-by-side comparison of our experimental RSSI model developed with the work of [10]. Measured RSSI follows the general trend of their model.

D. Determination of Pathloss Exponent

To determine the path loss exponent (n), we made use of the log distance equation model presented in Equation 1, with path loss exponent n, as the subject. This is presented in Equation 2.

$$RSSI = RSSI_0 - 10nlog_{10}\frac{d}{d_0} \qquad (1)$$

Where RSSI = Received Signal Strength

$RSSI_0$ = RSSI at 1m, which is given as -20.17dBm from literature.

n = path loss exponent

d= distance of test point

d_0 = reference distance = 1m

$$n = \frac{RSSI - RSSI_0}{10log_{10}\frac{d}{d_0}} \qquad (2)$$

n was calculated, averaged from the RSSI at the various test points and corresponding distances and determined to be *3.048*, for the study environment.

E. Comparison with Theoretical Propagation Model

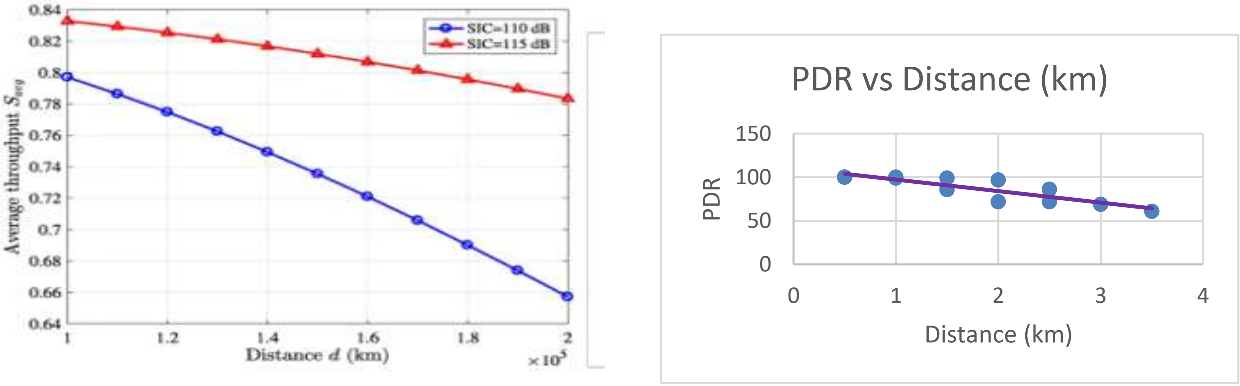

Fig. 5: PDR vs distance models side by side

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Fig. 5 shows a side-by-side comparison of our experimental PDR vs distance model developed with the work of [7]. Since PDR is highly correlated with throughput, there is strong correlation with their work as their plot shows throughput versus distance. Both models represent distance in the same units of kilometers.

This comparison highlights the importance of our conducted local field test, as other theoretical models, though capturing behavioral characteristics, may not adequately represent propagation challenges in specific African urban environments.

V. CONCLUSION

In this paper, we evaluated the packet delivery ratio (PDR) performance of LoRaWAN networks in an urban area of a tropical region. We conducted experiments around the test area, which is Benin City in Edo State, Nigeria, and we obtained parameters such as distance, RSSI, height above sea level(altitude) and packets sent and received, from which the secondary parameter PDR was derived. We created a dataset of our readings and applied machine learning and deep learning models to our data to see if we could predict PDR based on the parameters measured. Two models came out best after being evaluated using RMSE:

Multiple Linear Regression Model and Deep Learning model with a 5.942 and 7.820 error rate, respectively. We also determined the path loss exponent as 3.048 for the test area. The results obtained showed that LoRaWAN technology can be successfully deployed within the test area, and we have determined key parameters for determining RSSI for the test environment, as well as Machine Learning Models that can be used to predict packet success rates with losses less than 8%. Future work should embrace using more data points and may also consider the use of different spread factors, as well as more nLoS scenarios.

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