Comparing and Adapting Propagation Models for LoRa Networks

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***Abstract*—In a wireless network, understanding the spatio-temporal propagation of a radio signal and its attenuation over distance has always been a great concern. However, to set up an efficient network with these needs, it is imperative to have a good characterization of the signal propagation over the deployment environment. The contribution of this paper is twofold. First, we study, select and test some of existing signal propagation models on a LoRa network in order to see which model best fits LoRa signal propagation behavior. Second, we empirically optimize the best model from the first phase. The resulting model is then tested and validated in another real-world environment and compared to other models already experimented for LoRa networks. The Hata model is found in the first phase to show more accurate results and is therefore adapted using real measured data. The adapted model from Hata is then tested and validated with another and larger data set. Comparisons with Lee and Oulu models that have been used in previous real LoRa networks studies show that our adapted model can provide more accurate predictions to assist LoRa network deployment campaigns.**

***Index Terms*—LoRa, path loss model, LPWAN, Internet-of-Thing,**

I. Introduction

In a wireless network, understanding the spatio-temporal propagation of a radio signal and its attenuation over distance has always been a great concern. However, to set up an efficient network with these needs, it is imperative to have a good characterization of the signal propagation over the deployment environment. A way to characterize signal propagation is to model path-loss over distance in all direction of the propagation environment. A path-loss is the power loss involved in transmission between a transmitter and a receiver. In a real deployment scenario, a good path-loss model can increase the efficiency of a number of services, reduce undesirable power losses, increase coverage area and determine the best arrangement of gateways

Since Friis's model [1] that defines signal behavior in free space, there are myriad of schemes that attempt to model signal propagation over different scenarios. These existing propagation models can be housed in three categories. The first category contains theoretical models that are purely analytical models derived from the theory of ideal propagation of the electromagnetic wave. In this category, we can have models such as free-space path loss (FSPL) and plane earth propagation model [1], [2]. The problem with these models is that the ideal assumptions they make never happen in a real deployment. The second category includes empirical models based on measurements and the use of statistical properties. These models are not very accurate, but they are simple to set up. As examples, we have Okumura [3], Hata [4], Cost-Hata [5], Ericsson [6], and ECC-33 [7]. The third category is for deterministic models that can be very accurate but usually require accurate geometry information about the deployment environment. Hence, they are very computational and take time to design and set up. Ikegami model [8] and Ray Tracing [9] are part of this category. For more details the readers can refer to [2] which gives an overview of existing propagation models and propose new taxonomy for path-loss models.

All these models are well studied and most of them are implemented in many network simulators but mainly for the traditional wireless network. Some recent works aim at studying and adapting existing propagation models or design new ones for LoRa networks. The most studied model for LoRa is the log-distance path-loss model. It is implemented in many LoRa simulators developed recently such as LoRaSim by Voigt in [10] for studying LoRa inter-network interferences and the one developed by Rahmadhani and Fernando in [11] for studying LoRaWAN frame collision. However, the log-distance model is not very accurate for LoRa, especially in outdoor conditions. In [12], Hosseinzadeh et *al.* developed a new model for LoRa in outdoor-indoor scenario. The model proposed by the authors is a hybrid model that comprises an Artificial Neural Network (ANN) and an optimized Multi-Wall Model (MWM). They compare their model to log-distance and COST231 models. They conclude that log-distance and COST231 models do not yield an accurate estimation of propagation characteristics for outdoor-indoor scenarios. Petajajarvi et *al.* deduct a model using a linear polynomial fitting approach on measurements realized in the city of Oulu in Finland on an 868MHz LoRa network [13]. The model is only compared with Free Space Path Loss (FSPL) which is not a very proper evaluation. Nevertheless, the same model is experienced in Dortmund, Germany on both 433MHz and 868MHz LoRa networks and compared to five other models (Hata, 3GPP, ITU, FSPL, Winner+) but few discussions were given about this comparison [14]. Linka et *al.* in [15] study the Oulu model with Longley-Rice Irregular Terrain Model compared to FSPL.

Their study concludes that there is no perfect model and it is then necessary to assess whether false positives or false negatives are more important for the deployment of LPWANs. In [16], Dobrilović et *al.* analyse Lee propagation model adaptability on LoRa and propose an optimization tested on an 868MHz LoRa network in an urban area. They do tests in different environments and conclude that Lee propagation model is accurate enough to be used for LoRa, but they have not made any comparison with other propagation models.

The contribution of this paper is twofold. First, we study, select and test of some existing signal propagation models on a LoRa network in order to see which model best fits LoRa signal propagation behavior. Second, we empirically optimize the best model from the first phase. The resulting model is then tested and validated in another real-world environment and compared to other models already experimented for LoRa networks.

The rest of this paper is organized as follows. Section II discusses on the applicability to LoRa of existing models and define some model selection guidelines. Section III describes the experiment and measurement setup. An analysis and a discussion on the results of the experiments are provided. Section IV presents the empirical optimization process and tested the resulting model in another different real-world environment. Conclusions and future works are given in Section V.

II. EXPERIMENTED PROPAGATION MODELS

The following statements can be derived from the existing works:

- Log-distance model is the most used model in simulations. To the best of our knowledge, there is no study in a real LoRa network deployment;
- among the well-known existing model only Lee propagation model has been tested on a real LoRa network, but no comparison with other models has been made;
- until now, the only model derived from LoRa signal measurements is the Oulu model [13] and it has only been compared to the free space model.

Therefore, we adopt the following approach to try to find the model that best fits LoRa signal behavior:

1) first, identify among existing propagation models those that can be applied to a LoRa network based on some criteria according to the models' assumption parameters;
2) second, perform experiments to compare the selected models and find which one provides the best estimations compared to the measured data;
3) third, try to optimize the best fit model from measured data;
4) finally, test the optimized model in different environments and compare it with Oulu and Lee models.

A. Applicability of models and selection guidelines

All existing signal propagation models cannot be represented here. We try to consider the most studied and most used in existing network planning tools and simulators. In addition, as the most common deployment scenarios for LoRa is an outdoor scenario, we only select model suitable for an outdoor deployment. Then, most importantly, as each model uses parameters and assumptions, we select models whose parameters and assumptions are compatible with an outdoor LoRa scenario. The most important parameters being the frequency, the distance, the height of the gateway and the height of the end-device's antenna.

1) **Frequency** remains a critical parameter for models applicability. As current LoRa networks only operate in sub-GHz unlicensed band (e.g. 433, 868, and 915 MHz) only models with compatible frequency interval are selected. Note that some models can take into account a frequency correction factor.
2) **Distance** is also a key parameter as most existing models define a distance validity range. For example, for Okumura and Hata, the minimum distance between the gateway and the end-device must be 1 km. As the main advantage of LoRa being long-range, typical deployments are usually well over 1 km. However, in [17], the author showed that the Hata model can also predict path-loss over distances less than 600 m. Their study was for frequency 1800 MHz but a frequency correction factor can be used for other frequencies. Nisirat et *al.* [18] also proposed a modified Hata model when distances are less than 1 km.
3) **Height of the Gateway** in most of existing models needs to be above 10 m. This is usually the case for large-scale LoRa network deployment scenarios (e.g. smart cities). However, as LoRa is also deployed in smaller scale scenarios such as farms the gateway is rarely located above 10 m. It can be interesting to see if these models can provide meaningful results for heights below 10 m.
4) **Height of the end-device** is not too critical since most models consider the height of the device's antenna between 1m and 3m which is the case in most common scenarios.

Taking into account these aspects, we select four models: Log-distance, Hata, SUI, and Ericsson; the details of these models can be found respectively in [4], [6], [19], [20].

B. Selected models

1) Hata model: Hata model is derived from Okumura model [3]. It establishes empirical mathematical relationships to describe the graphical information given by Okumura. It extends Okumura model for urban, suburban and also open rural areas. Hata model is applicable only over quasi-smooth terrain. The base model of Hata is built for an urban area. The suburban and open rural areas are derived from this model. The following equations present Hata model formulas [4]:

- Urban area

$$L_{urban} = A - a(h_{ed}) + B\log_{10}(d) \quad (1)$$

where

– small and medium town:

$$a(h_{ed}) = 0.8 + (1.1\log_{10}(f) - 0.7)h_{ed} - 1.56\log_{10}(f) \quad (2)$$

– large town:

$$a(h_{ed}) = \begin{cases} \bullet\ 8.29(\log_{10}(1.54h_{ed}))^2 - 1.1 \\ \text{if } 150<f<200 \\ \bullet\ 3.2(\log_{10}(11.75h_{ed}))^2 - 4.97 \\ \text{if } 200<f<1500 \end{cases}$$

and

$$A = 69.55 + 26.16\log_{10}(f) - 13.82\log_{10}(h_{gw}) \quad (3)$$

$$B = 44.9 - 6.55\log_{10}(h_{gw}) \quad (4)$$

- suburban area

$$L_{suburban} = L_{urban} - 2(\log_{10}(f/28))^2 - 5.4 \quad (5)$$

- open rural area

$$L_{open} = L_{urban} - 4.78(\log_{10}(f))^2 + 18.33(\log_{10}(f)) - 40.94 \quad (6)$$

$a(h_{ed})$ in suburban and rural areas is the same as for urban areas (small and medium city). L_{urban}, $L_{suburban}$ and L_{open} are in dB, f in MHz, h_{gw} and h_{ed} in m, and d in km.

2) Log-distance path loss model: Log-distance path loss is a theoretical and measurement-based propagation model. It indicates that the average received signal power decreases logarithmically with distance in radio channels [19]. This model is derived from Friis's model FSPL. While FSPL is for line-of-sight (LoS) path loss in a free space environment, the log-distance model is used to accommodate different environments taking into account all other losses due to signal blockage like trees, buildings, hills, etc. The following equation defines the model.

$$PL_{dB} = \overline{PL_0} + 10\eta\log_{10}(d/d_0) + X_\sigma \quad (7)$$

Where PL_{dB} is the loss incurred by the transmitted signal during the propagation (expressed in dB). $\overline{PL_0}$ denotes the path loss at the reference point d_0 which can be between 1 and 10 m in a micro area or 1 km in larger areas. $\overline{PL_0}$ can be deducted from Friis's model or by a regression fitting of the data from measurements in the deployment environment. η is the path loss exponent with a value between 2 to 6 depending on the deployment environment. d is the distance between the gateway and the end-device. X_σ represents noises due to signal fading caused by the presence of obstacles between the transmitter and the receiver. If there is no signal fading X_σ is zero and the model is called log-distance path loss propagation model. However, if there is signal fading caused by large obstacles (mountains, buildings, etc.) known as shadow fading or slow fading, then X_σ has Gaussian distribution with σ standard deviation in dB. In this case, the model is known as log-normal shadowing. For fast fading that are due to multipath propagation effects, the corresponding gain can be modeled as random variable with Ricean or Rayleigh distribution depending on whether the LoS component dominates the other components (multipath) of the signal or not.

3) SUI model: Stanford University Interim (SUI) model is developed under the Institute of Electrical and Electronics Engineers (IEEE) 802.16 Broadband Wireless Access Working Group [19], [20]. In this propagation model, three different types of terrains or areas, A, B or C, are considered. Terrain A represents an area with highest path loss typical of very densely populated region. Terrain B represents an area with moderate path loss found in suburban environments. Terrain C is suitable for flat terrains with rare vegetation where path loss is the lowest [6], [21].

$$PL = A + 10\gamma\log_{10}(d/d_0) + X_f + X_h + s \quad (8)$$

Where d (in meter) is the distance between the base station and the receiving antenna, d_0=100 m is the reference distance, X_f is a correction factor for frequency above 2 GHz, X_h is a correction factor for the receiver antenna height and s is a correction factor for shadowing because of trees and other clutters on the propagation path. Parameter A is the free space path loss at the reference point d_0.

$$A = 20\log_{10}(4\pi d_0/\lambda) \quad (9)$$

The path loss exponent γ is given by

$$\gamma = a - bh_B + c/h_B \quad (10)$$

The following table presents SUI parameters for the different terrain type.

TABLE I
SUI MODEL'S TERRAIN TYPE

Model parameter	**Terrain A**	**Terrain B**	**Terrain C**
a	4.6	4.0	3.6
b(m^{-1})	0.0075	0.0065	0.005
b(m)	12.6	17.1	20

The following equations give the correction factors for the operating frequency and for the receiver antenna height of the model.

$$X_f = 6.0\log_{10}(f/2000) \quad (11)$$

and,

$$X_h = -10.8\log_{10}(h_r/2000) \text{ for terrain type A and B} \quad (12)$$

$$X_h = -20\log_{10}(h_r/2000) \text{ for terrain type C} \quad (13)$$

f is the frequency in MHz and h_r is the receiver antenna height in meter. The SUI model is used for path loss prediction in rural, suburban, and urban environments.

4) Ericsson model: This model has been implemented by Ericsson as an extension of the Hata model with adjustable parameters according to a given deployment scenario [19]. The path loss is described as follows:

$$PL = a_0 + a_1 \log_{10}(d) + a_2 \log_{10}(h_B) + a_3 \log_{10}(h_B) \log_{10}(d) - 3.2(\log_{10}(11.75 h_r))^2 + g(f) \quad (14)$$

Where *g(f)* is given by :

$$g(f) = 44.49 \log_{10}(f) - 4.78(\log_{10}(f))^2 \quad (15)$$

Parameters a_0, a_1, a_2 and a_3 are constants that can be changed to better reflect specific propagation conditions. Default values are: a_0=36.2, a_1=30.2, a_2=-12.0 and a_3=0.1.

III. Experiment and measurement setup

A. Network setup and measurements

For the experiments, we set up a LoRa network based on our low-cost LoRa IoT platform [22] that has also been deployed in many agriculture pilot applications in the context of the EU H2020 WAZIUP project in many African countries, as well as for other researches on LPWAN [23]–[26].

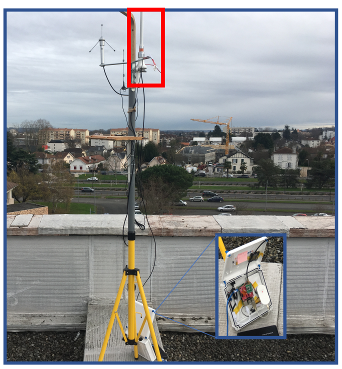

Fig. 1. Deployed gateway in University of Pau

TABLE II
Gateway and end-device configurations

Parameters	Gateway	End-device
LoRa module	SX1301-based	RFM95W
Transmission Power	N/A	14dBm
LoRa SF,BW	SF12BW125	SF12BW125
Frequency	865.2MHz	865.2MHz
Antenna height	15.6m	1.10m
Antenna gain	5dBi	2dBi
Board	RaspberryPi 3B	Arduino Pro Mini

The measurement campaign is realized in Pau city (France) around the university. The environment is a urban-like area. A gateway with a 5 dBi antenna is placed on the roof of the science department building of the university at 15.6 m height (see Fig. 7). An end-device with a GPS module and a small 2 dBi quarter-wave antenna sends its position to the gateway every 5 seconds. The gateway stores both RSSI and SNR of all received messages. The table II summarizes the configuration

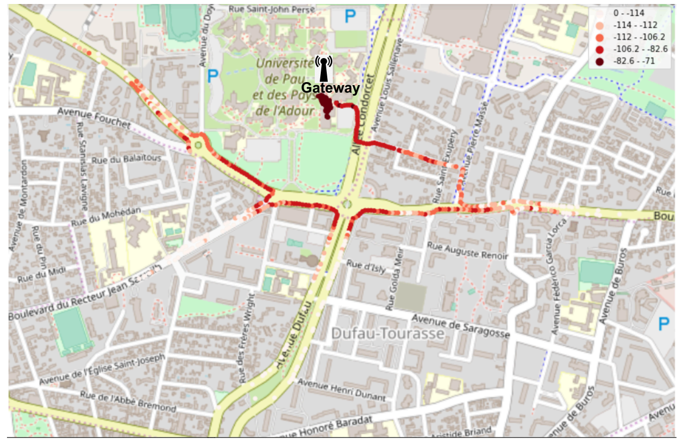

Fig. 2. Measurement points and Heatmap of RSSI (dBm) variations in PAU

of the gateway and the end-device for the experiment setup. Fig. 2 shows all the collected points.

To remove noise from the raw RSSI values which are mainly due to multipath effects, we filter the raw data with a Moving Average (MA) filter implemented using convolution. Fig. 3 shows the raw RSSI data and the filtered one.

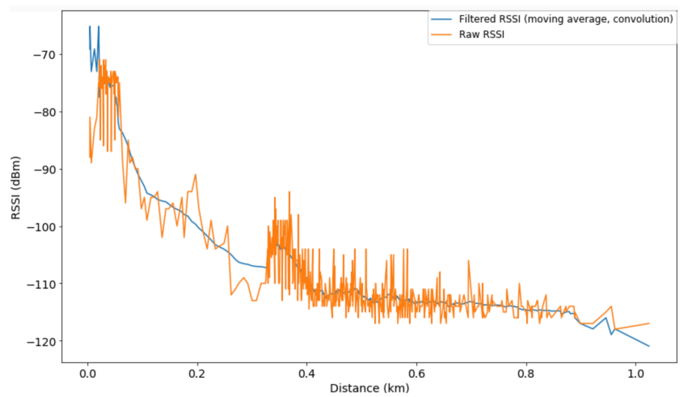

Fig. 3. Filltered raw RSSI data using moving average filter (convolution) (Pau experiment)

B. Result analysis and discussion

With the measured data, we tested 4 models: Hata, Log-distance, SUI, and Ericsson models. According to the experiment environment (Pau city), we chose specific values for the path loss parameters for each model, as shown in Table III.

TABLE III
Selected models' parameters

Mdels	Parameter chosen values
Log-distance	PL exponent = 3.5 / PL_0 = Friis at d_0 = 1 km
Hata	Urban version / A = Friis at 1 km
SUI	Terrain type B / Standard deviation s = 8.2
Ericsson	Default values

We computed the path loss from measured data and the one predicted by each model. The results are shown in Fig. 4.

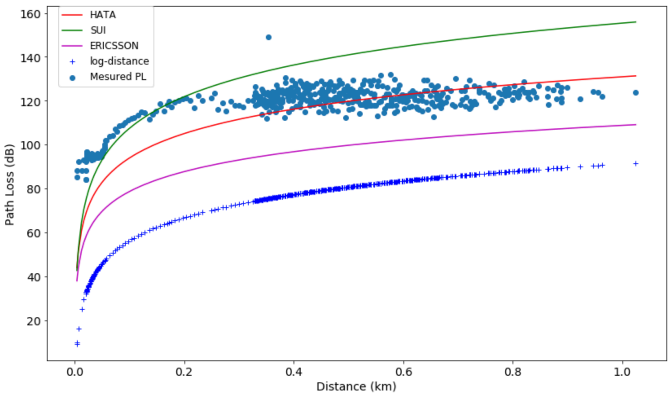

Fig. 4. Path loss measures in urban (University Pau)

Among the selected path loss prediction models the Hata model's predicted values has the smallest Root Mean Square Error (RMSE) of 10.63 while the log-distance model shows the largest RMSE of 44.88. SUI and Ericsson models have RMSE of 19.21 and 24.85 respectively. We will therefore try to adapt and optimize the Hata model for LoRa networks.

IV. Path loss model adaptation and validation

A. Hata adaptation and optimization

The Hata model depends on three basic parameters: the initial offset parameter, the initial system design parameter and the slope of the model's curve. The system design changes from a deployment to another because it depends on the installation: frequency, the height of the antenna, etc.

$$L = 69.55 + 26.16\log_{10}(f) - 13.82\log_{10}(h_{gw}) - a(h_{ed}) + 44.9 - 6.55\log_{10}(h_{gw})\log_{10}(d) \tag{16}$$

From Eq. 16 we can derive the three basic parameters:

$$L_{offset} = 69.55 \tag{17}$$

$$L_{system} = 26.16\log_{10}(f) - 13.82\log_{10}(h_{gw}) - a(h_{ed}) \tag{18}$$

$$L_{slope} = 44.9 - 6.55\log_{10}(h_{gw}) \tag{19}$$

Hence, Eq. 16 can be rewritten as follows:

$$L = L_{offset} + L_{system} + L_{slope}\log_{10}(d) \tag{20}$$

As L_{system} depends on the frequency (f) and the antenna heights (end-device: h_{ed}, gateway: h_{gw}) and therefore changes from a setup to another, it is suggested for tuning to adapt the offset which does not depend on the deployment and the slope of the model's curve. We use least square (LS) fitting method on the measured data to find the optimum values of these parameters. First, Eq. 20 can be rewritten as follows:

$$L = a + bX \tag{21}$$

Where a = $L_{offset} + L_{system}$, b = L_{slope} and X = $\log_{10}(d)$. LS optimization consists in finding the optimum values $\tilde{a}$ and $\tilde{b}$ of a and b that minimize the following equation:

$$min\ LS(a,b) = \sum_{i=1}^{n}(y_i - (a + bx_i))^2 \tag{22}$$

Where y_i is the measured path loss at distance x_i, $(a + bx_i)$ the estimated path loss at distance x_i, and n the size of the experiment set. After finding $\tilde{a}$ and $\tilde{b}$ we can then derive the optimum offset and slope:

$$\tilde{L}_{offset} = \tilde{a} - L_{system}; \quad \tilde{L}_{slope} = \tilde{b} \tag{23}$$

We then use limited-memory BFGS optimization algorithm to minimize the least square function (LS(a,b)). After fitting with data from the experiment in Pau, we find: $\tilde{a}$ = 122 and $\tilde{b}$ = 16. By replacing $\tilde{L}_{offset}$ and $\tilde{L}_{slope}$ in Eq. 20, we obtain the following simplified model that we name HataLoRa:

$$HataLoRa(dB) = 122 + 16\log_{10}(d/d_0) \tag{24}$$

where d is the distance in km and d_0 the reference point at 1 km.

B. Test and validation

To test our adapted model derived from Hata model, we compare it with measurements obtained from a more complex and wider environment test campaign performed in Saint-Louis (Senegal). We will then also compare the results with Oulu and Lee models that have been previously used in studies based on real LoRa networks as previously mentioned.

1) Network setup and measurements: The test and validation experiment is realized in Saint-Louis, Senegal, at the Gaston Berger University. The university is located at about 14 km north from Saint-Louis city and the test area can be considered as suburban with administrative and teaching buildings, student residential areas and some unbuilt areas with trees. The university is surrounded on its south and south-east part by a suburban area with small houses and business building; and on its north and Northwest part by a rural area with farms, fields, villages, and hilly terrains. The gateway is placed on the highest location of the university which is the top of the library tower at 44.6m (see Fig. 5).

Fig. 5. Deployed gateway in Saint-Louis

The end-device is attached on a car driving at about 30 km/h and it is programmed to send its position to the gateway every 5 s. Fig. 6 shows in a map all the collected positions. Except for the gateway's height, all parameters are similar to those shown in Table II.

Fig. 6. Measurement points and Heatmap of RSSI (dBm) variations in Saint-Louis

As in the previous experiment, the raw RSSI values are first filtered before applying the proposed models.

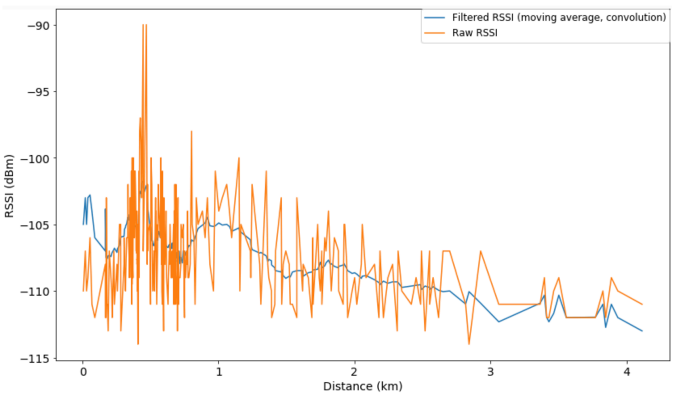

Fig. 7. Filltered raw RSSI data using moving average filter (convolution) (Saint-Louis experiment)

2) Results and discussion: Our adapted model is now compared to Lee and Oulu models. Lee model has been studied on an 868MHz LoRa network in Zrenjanin city in [16]. Oulu model is derived from measurements in a LoRa network in the city of Oulu (car version) using linear polynomial fitting. The result illustrated in Fig. 8 shows that the path loss in all three models goes far beyond the measured path loss. However, the RMSEs for all the three models are relatively small making them suitable for LoRa network deployment planning. Our adapted model (HataLoRa) computed the smallest path loss values with an RMSE of 10.84 against 13.02 for Oulu model and 16.62 for Lee model.

From the observed shape of the curves, we can see that (i) the path loss in all three models goes far beyond the measured path loss and (ii) the measured path loss does not seem to increase much with distance. Regarding the last observation it is usually assumed that the power of a signal decreases with distance. However, this assumption is not always observed because it is derived from the theory of ideal propagation of the electromagnetic wave. In real deployment, the variation of the signal is influenced by many factors of the environment in

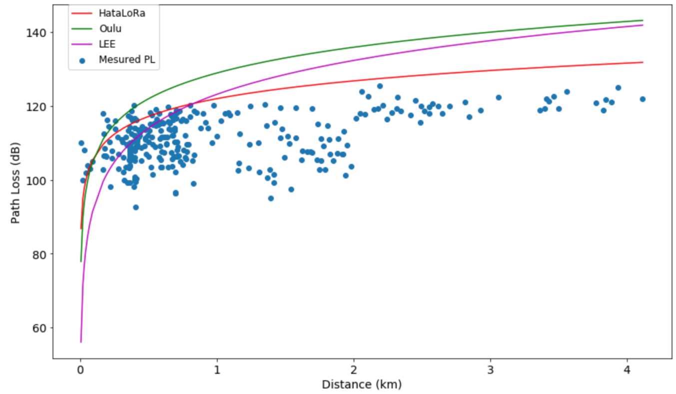

Fig. 8. Path loss measures in sub-urban (GB University)

which the signal propagates therefore predicting the behavior of a signal in complex environments is very difficult. In our test, the gateway is located at the highest point inside the university which is surrounded by buildings, amphi-theaters, offices, trees, and people. As the transmitting device moved around, the signal between the device and the gateway has to go through various area types, as illustrated in Fig. 9, that can have a severe impact on the signal quality at the gateway.

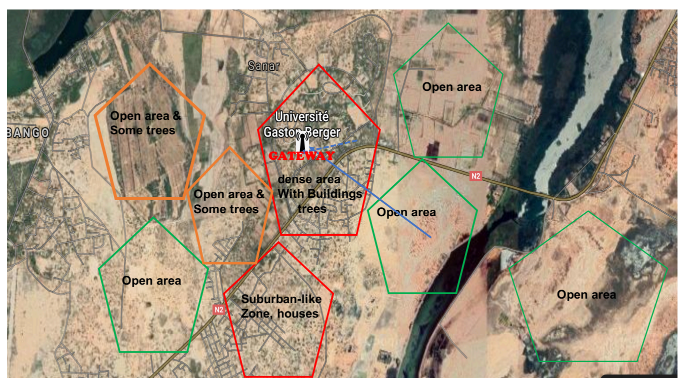

Fig. 9. Various area types around the gateway (Saint-Louis)

Therefore, in Fig. 8, the fact that the path loss does not seem to increase when distance goes higher can be explained by a very high path loss for measured data in locations close to the gateway. The path loss distribution plotted in Fig. 10 shows that 80% of the values, for distances under 1km, are between 110dB and 113dB which is very high for these distances. From Fig. 11 which links the RSSI variation to the Fresnel zone and the elevation of obstacles between a location and the gateway, we can observe that obstacles are very high and most of them reside in the 60% of the Fresnel zone that need good clearance in order to have good signal. At locations beyond 1km, Fig. 11 shows better LoS condition and compared to measurements reported in [13] and [16], at same distances (between 2 and 5 km), the signal similarity is high.

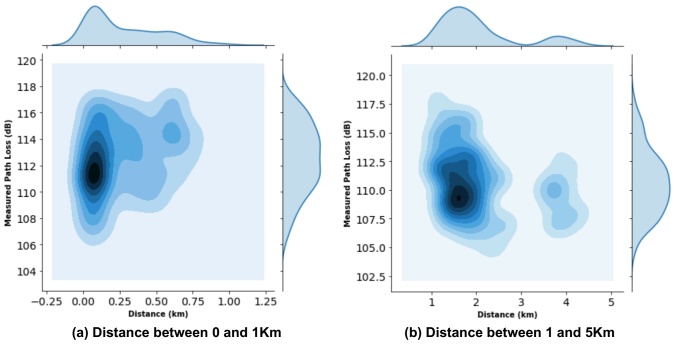

Fig. 10. Measured path loss distribution over distances (Saint-Louis)

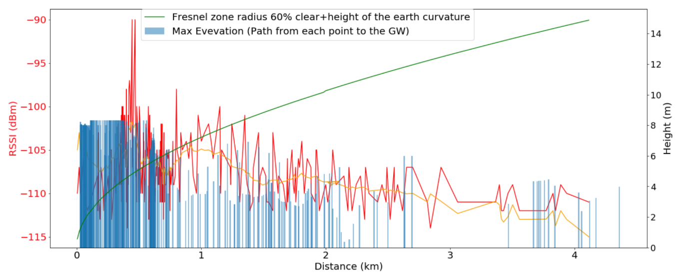

Fig. 11. RSSI variation vs link path elevation and Fresnel zone radius 60% clear+height of the earth curvature

V. Conclusions

In this paper, we study LoRa signal propagation models. We conducted real measures in Pau city to compare selected signal propagation models that can be applied to a LoRa network: Hata, log-distance, SUI, and Ericsson. As Hata model showed more accurate predicted values, we then try to adapt and optimize the Hata model by taking into account the real measures of Pau city. The adapted model is then tested and validated with another data set. Comparisons with Lee and Oulu models that have been used in previous real LoRa networks studies show that our adapted model (HataLoRa) can provide more accurate predictions to assist LoRa network deployment campaigns. In future works, the adapted model will be used to obtain better RSSI-based localization estimates for low-cost cattle localization applications.

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