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Log Distance Path Loss Model: Application and Improvement for Sub 5 GHz Rural Fixed Wireless Networks

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ABSTRACT The study of radio signal propagation path loss (PL) is important for planning, designing and evaluating the performance of radio communication networks. However, the state-of-the-art in PL modelling for fixed wireless networks in rural environments is still ill-equipped for making accurate predictions. This paper explores the application of the log distance PL model to heterogeneous fixed wireless networks in harsh rural propagation conditions. This model is then extended and optimized to improve its accuracy. In particular, the dataset is classified according to many criteria, radio links are split into many intervals according to their distances, antenna heights and elevations are integrated into its formula and long-term extreme seasonal variations are considered. Our study uses a wide set of measurements from the fixed wireless networks of a wireless internet service provider in rural regions of Canada. The proposed modifications improve the accuracy by 7 to 15 dB in terms of the root mean squared error.

INDEX TERMS Radio signal propagation, propagation empirical models, path loss, seasonal effects, log distance model.

I. INTRODUCTION

Wireless communication systems have been developed recently to become the cornerstone of modern society. These ubiquitous and pervasive technologies are facilitating a range of activities by providing permanent access to services, information and commodities. Wireless systems are an access solution for deployment in difficult conditions often found in rural environments, since they offer a fair compromise between performance and cost. New applications' requirements are sometimes hard to satisfy, especially in difficult environmental conditions of rural areas, where it is hard to accurately estimate the radio signal attenuation due to the random nature of the density and seasonal growth of vegetation. This attenuation causes radio signal path loss (PL) and limits its coverage range and quality of service (QoS). To take up this challenge, PL models are developed and tuned according to the investigated environment for planning, designing and evaluating the performance of wireless systems.

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Many PL models are available in the literature, such as the free space and log distance (LD) models [1], [2]. This study examines the application of the LD model to heterogeneous wireless-to-the-home (WTTH) networks, as this model is widely and easily used with less resources and complexity [3]. The data for the model are from the fixed wireless networks (FWNs) of an internet service provider (ISP) in two rural regions of Canada. Two obstruction profiles are available, namely direct line of sight (LOS) and non-LOS (NLOS) links, along with many frequency bands: 915 MHz, as well as 2.4, 3.65 and 5.8 GHz. Furthermore, we propose two modifications to the LD model in order to consider antenna heights and elevations.

The contributions of this research are:

- The accuracy of the LD model is investigated for heterogeneous FWN.
- The LD model is modified to improve its precision by splitting the signal path into many intervals, and by considering antennas' heights and elevations.
- We extend the improved LD model according to the seasonal variation in the radio signal propagation PL.

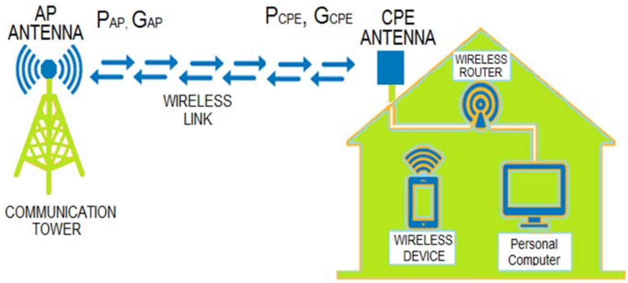

FIGURE 1. Example of the deployment of FWN.

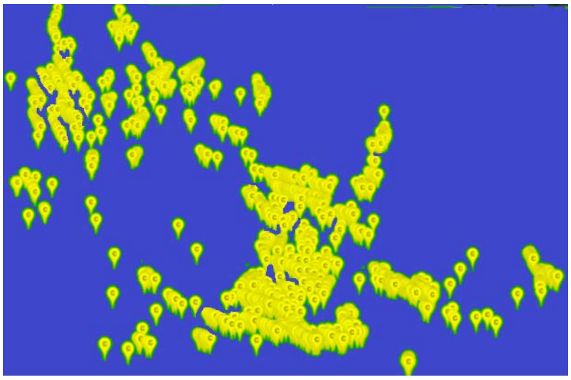

FIGURE 2. Radio links of SLSJ region.

- We extract its optimal parameters according to frequencies in the range of 900 MHz to 5.8 GHz, line of sight obstruction (LOS or NLOS) and seasons.

This paper is organized as follows: Section 2 discusses the related technical background, while Section 3 introduces the state-of-the-art. Next, Section 4 discusses the accuracy of the LD model as well as the proposed modifications, and Section 5 considers seasonal PL variation effects. Finally, conclusions are drawn in Section 6.

II. TECHNICAL BACKGROUND

A. NETWORK MODEL

The network model is shown in Fig. 1, where access points (APs) are connected via long-range Wi-Fi [4] or Long-Term Evolution (LTE) [5]. Each AP is connecting many Customer Premise Equipment (CPE) units to the Internet. A CPE can be installed on any high place such as roofs or trees. Then, it is wired to the users' indoor equipment. Many frequency bands are used for diverse radio signal penetration. Higher frequencies are mostly used for LOS links, whereas lower ones are used for NLOS links, as they have better penetration. The use of many AP and CPE antenna gains and radiated power diversifies the configurations of radio links. AP and CPE antenna heights depend on where they are installed, be it on towers, roofs or trees. The radio link distance d can be as great as 18 Km. More details are provided by [5] and [6].

B. MEASUREMENTS

The measurements are provided from a wide commercial FWNs of a wireless ISP for two different rural regions in Canada: Saguenay Lac Saint Jean (SLSJ) and Outaouais (OUT). Fig. 2 and 3 show the wireless links in these two locations, respectively. NLOS links principally encounter trees and perhaps some buildings, and the terrain is covered by hills, lakes and plains. Environmental conditions vary between two extremes: snowy, cold weather with evergreen trees in the winter and rainy, hot weather with leaves growth in the summer. Measurements are taken throughout the year in order to consider the seasonal long-term PL variation. Rain, snow falling and wind are not considered in this research since they are time-limited events. The measurements are collected periodically, then they are averaged to remove the fast fading effect. They include pertinent information for QoS characterization, such as data rates, signal-to-noise ratios, and so on.

FIGURE 3. Radio links of OUT region.

TABLE 1. Path loss exponent values [12].

Environment	Path loss exponent (n)
Free space	2
Urban area cellular radio	2.7 to 3.5
Shadowed urban cellular radio	3 to 5
Inside a building - line-of-sight	1.6 to 1.8
Obstructed in building	4 to 6
Obstructed in factory	2 to 3

Other pertinent information is collected, such as antenna heights and gains, GPS coordinates, distances, elevations, seasons, and obstruction levels. Since CPE nodes and APs are installed in high places, the moving targets and the ground reflection effects are neglected. All models are fitted with SLSJ measurements, then tested with OUT measurements to verify their generalizability.

The collected data are used to compute the measured PL via the Friis formula [2]:

$$P_r = P_t + G_t + G_r - L \tag{1}$$

where Pt and Pr are the transmitted and received power signals, respectively; and Gr and Gt are the receiver and transmitter antenna gains, respectively. L is the total PL and internal devices' (L_{int}) losses asgleaned from their data sheets. The PL is then given by:

$$PL = P_t + G_t + G_r - P_r - L_{int} \tag{2}$$

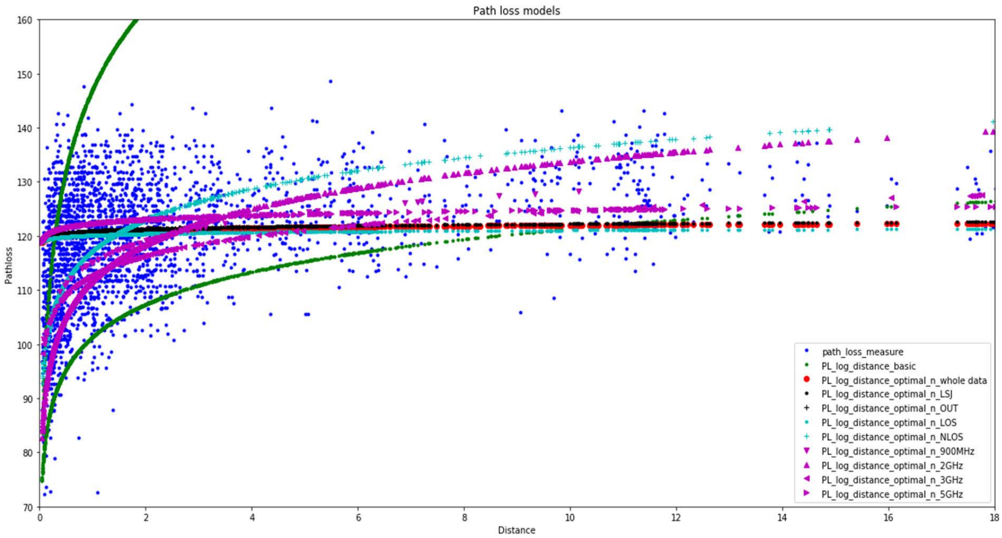

FIGURE 4. Accuracy comparison of the LD model classical application with model optimization through data classification.

C. PATH LOSS MODELS

Empirical models provide a fair trade-off between processing efficiency, accuracy and complexity [7]. The free-space model [8] is the simplest PL model. It is given by:

$$PL_{FS}= 20\log\frac{4\pi d}{\lambda} \tag{3}$$

where d is the link distance, and λ is the wavelength. It assumes that the signal attenuation is due to free space only.

Other PL models consider LOS obstruction, such as vegetation and buildings. The most well-known ones are: Cost231, Stanford University Interim, Ericson, Hata and Hata-Okumura [9]. Unfortunately, each model has its own boundaries and does not perfectly fit the measurements [10] and [11]. The LD model compute the PL of NLOS links. If PL_{d0} is the PL at distance d_0, then the PL at an arbitrary distance $d > d_0$ can be given by [12]:

$$PL_{LD} = PL_{d0} + 10n\log_{10}\left(\frac{d}{d_0}\right) \tag{4}$$

where n is the PL exponent, its values are given in Table 1. This model is called log normal shadowing when considering the shadowing effects χ due to obstructions [13]. The random variable χ follows a Gaussian distribution with a zero-mean and a standard deviation σ between 8.2 and 10.6 dB [14].

III. STATE-OF-THE-ART OF LOG DISTANCE PATH LOSS MODEL

The LD PL model is used in numerous applications, such as on-body PL modelling for ultra-wideband communications [15], drone aerial communications [16], mobile communication [17], [18], wireless sensor networks [13], [19], PL estimation in forested environments [20], and FWN [21], [22].

Many researchers have studied the existing PL models. The authors of [9] surveyed 60 years of continuous research. Other research focused on PL for fixed wireless communications. In [22], we compared ten PL models to the measurements taken on many thousands of fixed radio links and established a framework to derive and test a convenient PL model for FWNs in rural areas with an RMSE between 9 and 10 dB. In [23], the authors concluded that there is no ultimate PL model for all cases by analysing more than 30 models and by collecting data from a wide FWN in unlicensed bands. Phillips *et al.* analysed the performance of 28 PL models using the dataset of a rural wireless network in New Zealand [24]. They proved that available PL models are less accurate in rural environments with 12 dB RMSE of accuracy at best. In [3], the authors confirmed that PL models provide an accuracy of 8 to 9 dB RMSE, at best, in urban environments and almost 15 dB in rural ones. Milanović *et al.* compared the accuracy of the most widely used PL models in WiMAX applications at 3.5 GHz [25].

Existing studies have compared the accuracy of existing PL models, including the LD model, in various applications. Elechi *et al.* proved that LD performance is close to that of the Okumura model in 900 MHz applications [26]. Sharma *et al.* compared the LD model with other models in three different environments (urban, suburban and rural), and it had the best performance in rural areas [1]. In the experiment of Chebil *et al.*, the log normal shadowing model was the closest to measurements [17]. Also, the authors of [21] compared several PL models using 3.5 GHz FWN applications. They showed that LD was not the most accurate model but that it performed reasonably.Due to its performance, there have been many extensions of the LD model. Fendji *et al.* compared many modifications including the dual slop, log normal shadowing, partitioned and Liechty models for 2.4 GHz 802.11n wireless networks in rural areas [27]. They demonstrated that the Liechty model provides better precision and combined it with the dual slop model. Their measurements were taken from a USB wireless adapter, and the maximum distance was 600 m, with around twenty points

TABLE 2. PL exponents according to classification criteria.

		Region		Obstruction		Frequency (GHz)			
PL models	All	SLSJ	OUT	LOS	NLOS	0.915	2.4	3.65	5.8
LD	27.35	28.2	25.6	16.9	33.3	40.72	28.58	21.64	22.30
LD data splitting	11.00	11.7	9.7	12.4	11.1	7.91	13.39	9.45	12.36
Okumura Hata	17.4	18.7	14.8	19.5	15.2	14.1	16.5	20.2	18.9
Cost231_hata	18.1	19.5	15.0	20.5	15.4	14.5	16.5	21.3	20.6
SUI	19.3	19.9	17.9	20.5	18.0	16.8	19.0	20.9	19.8
Ericson	23.8	26.6	17.3	28.2	18.8	20.3	22.4	30.1	24.9
free_space	51.0	49.1	54.5	46.4	55.0	48.6	52.3	47.3	50.0
ECC 33	154.6	158.8	146.3	164.5	144.7	119.5	145.7	167.5	174.5
3GPP_TR_38.901	158.7	190.6	64.3	149.3	166.9	133.1	194.7	82.3	75.7

of measurement. Kelner *et al.* considered the antenna gains and directions [28]. The maximum distance did not exceed 400 m, and the PL was compared with other models for many gains and directions. Jeong *et al.* studied PL variations in the industrial, scientific and medical (ISM) bands for drone applications and they extended the LD model for aerial communications [16]. The horizontal distance range was between 10 and 70 m, and the altitude was between 1.5 and 101.5 m. Fernández *et al.* divided the radio link into two intervals, and each one had its own propagation exponent [29]. The LD model was fitted for digital TV applications in Lima, Peru and provided the best accuracy.

In conclusion, even if many researchers have studied the PL models for FWN, the LD model was not always included [23], [24], [25]. The few researchers who considered this model did not do so for FWN applications [1], [17] and they used limited coverage ranges [16], [27], [28].

IV. LOG DISTANCE MODEL MODIFICATIONS

A. LD MODEL APPLICATION

The accuracy of the LD model is based on the root-mean-square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(PL_i^{meas} - PL_i^{pred}\right)^2}{N}} \tag{5}$$

where N is the number of measurements, and PL_i^{pred} and PL_i^{meas} are the predicted and measured PLs, respectively. Table 2 presents the RMSE comparison of the LD model with the most well-known PL models by considering its standard configuration and its data-splitting optimization. Its RMSE varies between 17 and 40 dB, which is almost poor compared to the signal sensibility [6]. However, its data-splitting application is promising, as it improves the RMSE to 11 dB for the aggregated data.

B. LD OPTIMIZATION WITH DATA SPLITTING

To optimize the model parameters (n, d_0 and PL_{d0}), the measurements have been classified according to the following criteria: region, LOS and frequency bands. Table 2 outlines the accuracy comparison between the standard LD model and its optimization according to data splitting for all data, regions, obstruction levels and frequencies. Its accuracy is improved

TABLE 3. Accuracy of data splitting optimization, the RMSE is computed for all data aggregated.

Classification criteria	Path loss exponent
All data	0.133
Region	0.143
LOS	0.093
NLOS	1.915
915 MHz	1.309
2.4 GHz	2.197
3.65 GHz	1.173
5.8 GHz	0.255

TABLE 4. RMSE comparison among the standard LD model and the models with the proposed modifications.

Splitting criteria	RMSE
Classical application	27.35
All data	11
Region	11.007
Obstruction	11.78
Frequency band	12.63

considerably with data splitting, and the RMSE does not exceed 13 dB. Fig. 4 compares the PL measurements with the standard LD model and its optimization according to various data-splitting criteria. Table 3 summarizes the PL exponents, *n,* extracted with the least squares algorithm implemented via the curve fit function in the optimization module of SciPy [30]. The value extracted for Region is close to the one extracted for all data, which proves the generalizability of this model. Note that n increases with the obstruction level, and its low value for higher frequencies is justified by their use for LOS links. Table 4 summarizes the data splitting accuracy with an improvement of 16.35 dB RMSE.

C. MULTI-INTERVAL LOG DISTANCE (MILD) MODEL

As long-range Wi-Fi links are longer than 18 Km and the PL strongly depends on the distance of radio links, the dataset is divided according to the ascending link distances, into several intervals, to increase the accuracy. Then, each interval is independently optimized and has its own parameters by using the least squares algorithm implemented via the curve fit function in the optimization module of SciPy [30]. The total intervals' number is dynamically optimized to reduce the global RMSE. Hence, to assess the PL for a new radio link, the parameters of the interval including its distance are selected. The MILD expression is given by:

$$PL_{MILD} = PL_{d0,i} + 10n_i \log_{10}(\frac{d}{d_{0,i}}) \tag{6}$$

where $d_{0,i}$, $PL_{d0,i}$ and n_i are the ith interval's parameters, and the it^{h} interval includes the distance of the new radio link to be predicted.

Fig. 5 shows the optimization of the number of intervals. The optimal number is 10, and its RMSE is 10.1 dB, which

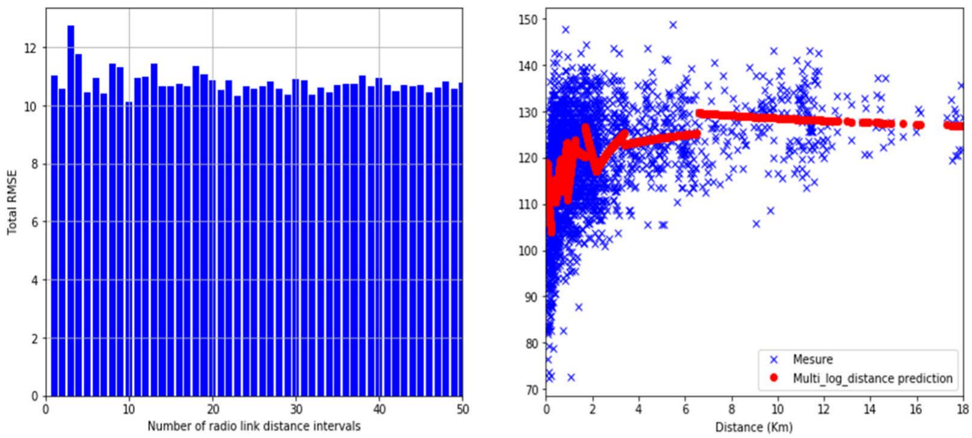

FIGURE 5. The figure on the left depicts the extraction of the optimal number of intervals that corresponds to the minimal RMSE. The figure on the right shows the PL of the MILD model.

TABLE 5. Comparison of the LDHE model by splitting the dataset acording to the obstruction.

LD model configuration	Path loss exponent	RMSE
Standard model	LOS, $n = 2$ NLOS, $n = 5$	27.35
Optimized exponent n	$n = 0.133$	11.006
LDH	$n_0 = 0.318$ $n_1 = -0.559$ $n_2 = 0.533$	10.871
LDHE	$n_0 = 0.975$ $n_1 = -0.267$ $n_2 = -0.653$	9.811

provides an improvement of 1 dB compared to the data classification optimization in Table 4. The overfitting of this model occurs if the number of intervals is increased above its optimum. Even if the RMSE continues to decrease, there are not enough samples to generalize for new links.

D. ANTENNA HEIGHT EFFECT: LOG DISTANCE HEIGHT (LDH)

The proposed modification integrates antenna height in order to consider implicitly the obstruction level for the radio links. Therefore, in addition to the reference distance d_0,two reference parameters are added for the AP and CPE antenna heights, namely h_AP_0 and h_CPE_0. Hence, two exponent values n_1 and n_2 are optimized, as in [30], for the AP and CPE antenna heights, respectively.

The new LD height (LDH) PL expression is given by:

$$PL_{LDH} = PL_{d0} + 10n_0 \log_{10}(\frac{d}{d_0}) + 10n_1 \log_{10}(\frac{h\_AP}{h\_AP_0}) + 10n_2 \log_{10}(\frac{h\_CPE}{h\_CPE_0}) \quad (7)$$

where h_AP and h_CPE are the AP and CPE antenna heights, respectively, for the new radio link to be predicted.

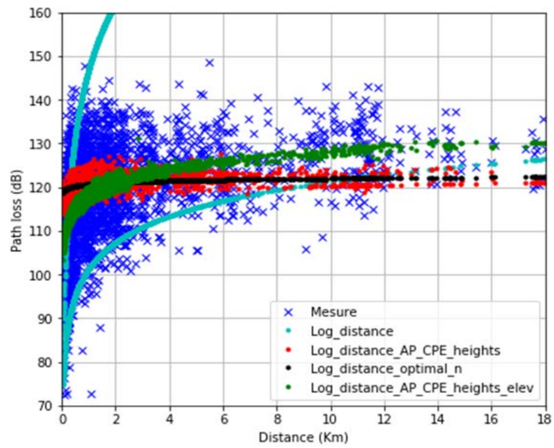

FIGURE 6. Comparison between the measurements, the standard LD, the optimized PL exponent, LDH and LDHE.

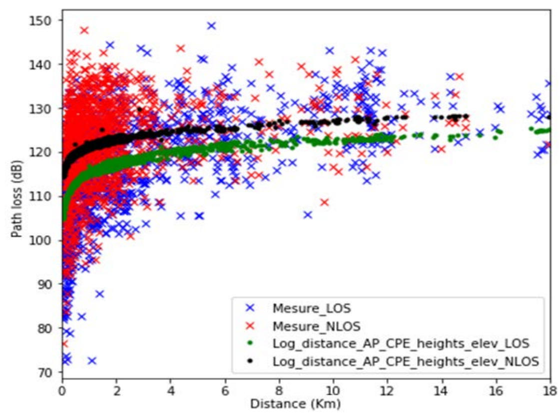

FIGURE 7. Comparison of the LDHE with the measurements done by splitting the dataset into LOS and NLOS links.

E. ANTENNA HEIGHT ELEVATION: LD HEIGHT ELEVATION (LDHE)

This new modification of the LD model considers antenna heights and elevations together to integrate the geographical relief into the PL estimation, since higher elevations have an important impact on the LOS. The LD height

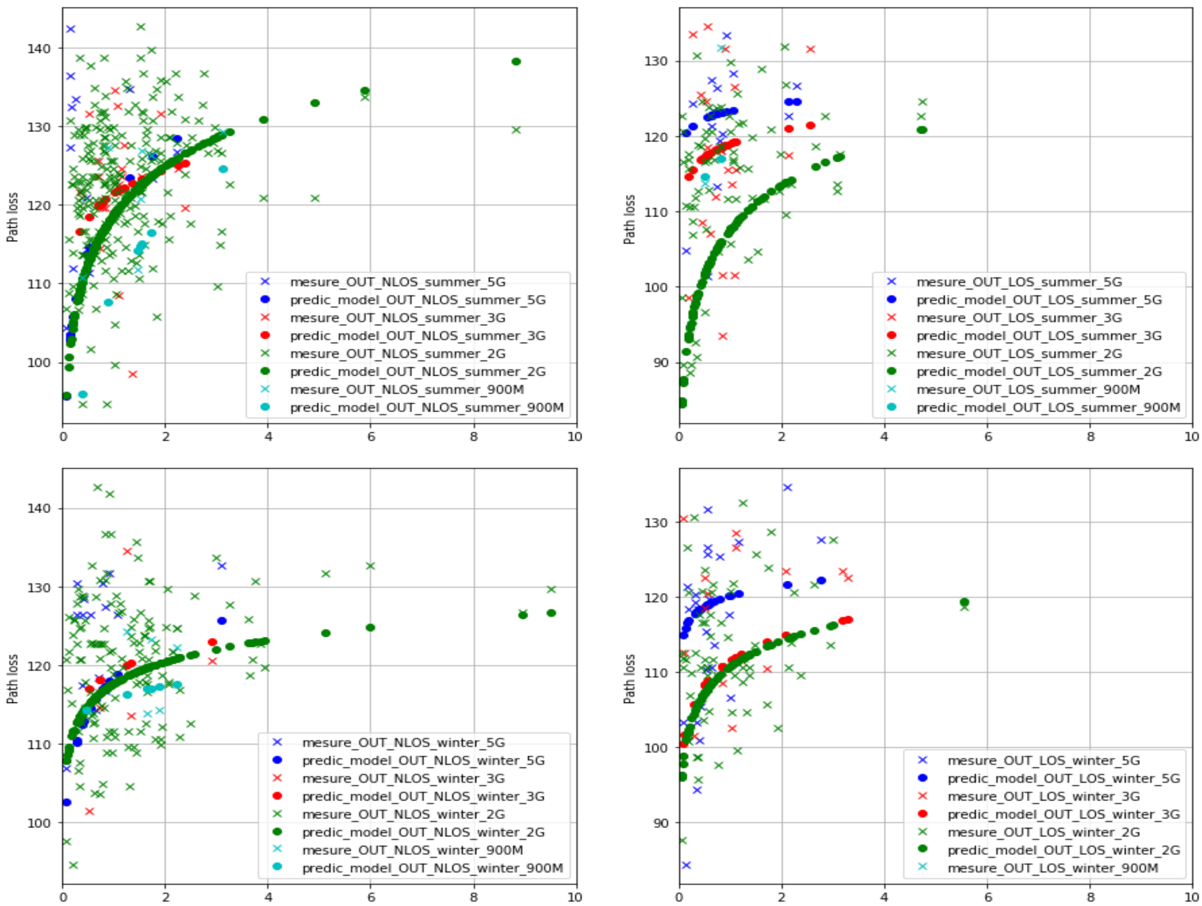

FIGURE 8. Comparison of LD model to measurements in the OUT region according to obstruction, frequency and season.

TABLE 6. Optimal PL exponents n extracted acording to obstruction, frequency and season for the LD model.

LDHE model	Path loss exponent	RMSE
LOS	$n_0 = 0.808$ $n_1 = -0.432$ $n_2 = 0.460$	11.21
NLOS	$n_0 = 0.525$ $n_1 = 0.207$ $n_2 = -0.518$	9.2
LOS and NLOS data aggregation	-	10.23

elevation (LDHE) formula is then given by:

$$PL_{LDHE} = PL_{d0} + 10n_0 \log_{10}(\frac{d}{d_0}) + 10n_1 \log_{10}(\frac{h\_AP + elev\_AP}{h\_AP_0}) + 10n_2 \log_{10}(\frac{h\_CPE + elev\_CPE}{h\_CPE_0}) \quad (8)$$

where elev_AP and elev_CPE are the AP and CPE antenna elevations, respectively, and n_0, n_1 and n_2 are optimized as in previous sections [30]. Comparison between the LDH and LDHE models

Table 5 compares the RMSEs of the two proposed LD model modifications and their corresponding PL exponents. It shows that the RMSE of the LDHE model is 1 dB better than that of the LDH model, 1.2 dB better than that of the data classification application model and 17.5 dB better than that of the standard LD model. The PL exponents of the standard LD are set according to state-of-the-art recommendations, whereas they are optimized freely for the other modifications via the least squares algorithm implemented with the curve fit function in the optimization module of SciPy [30].

Fig. 6 shows the PL comparison among the LD models. As the LDHE is the closest to the measurements, its accuracy is explored by splitting the dataset into LOS and NLOS links, as shown in Fig. 7. Note that the PL of the NLOS LDHE model is higher than that of the LOS one, which was anticipated since the radio signal is highly attenuated for NLOS links.

The RMSE and PL exponents (n_0, n_1 and n_2) of the LDHE model obtained by splitting the data according to obstruction level are illustrated in Table 6. The RMSEs for LOS and NLOS links are 11.21 and 9.2 dB, respectively. When the data is aggregated, the RMSE is 10.23, which is 1.5 dB better than the 11.78 RMSE for the LOS-NLOS exponent n optimization of the classical LD mode recorded in Table 4.

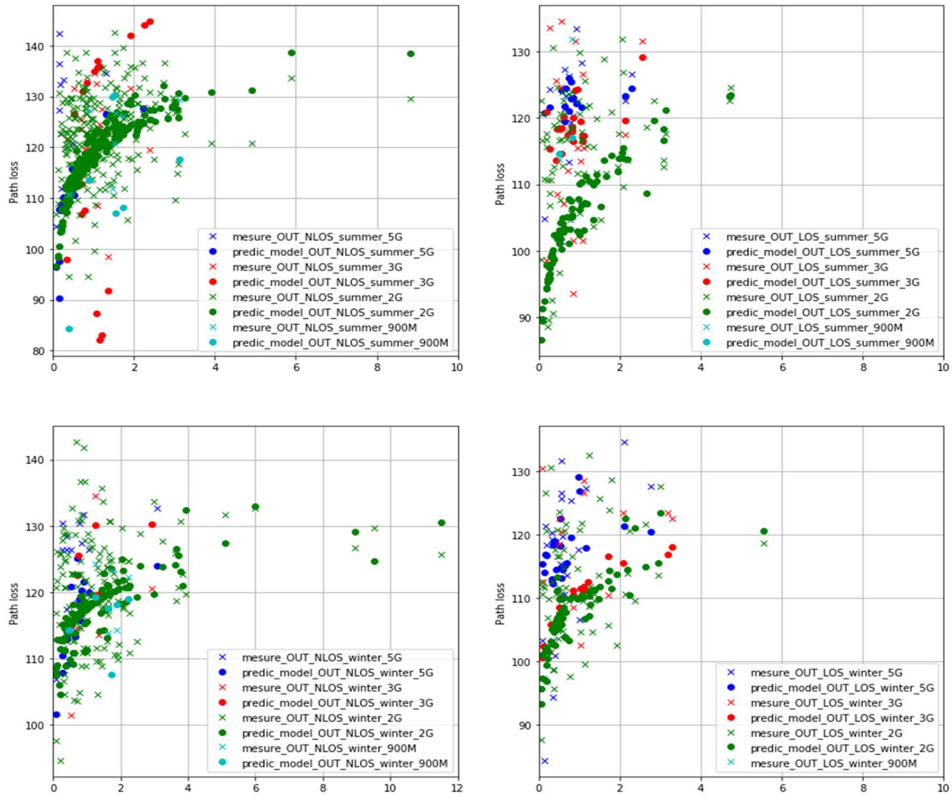

FIGURE 9. Comparison of LDH model with measurement in the OUT region according to obstruction, frequency and season.

TABLE 7. RMSE comparison of PL models (dB).

	NLOS summer	NLOS winter	LOS summer	LOS winter
5 GHz	2.152	1.482	0.349	0.477
3.65 GHz	1.019	0.795	0.598	1.079
2.4 GHz	2.055	0.916	1.962	1.160
900 MHz	3.115	0.485	1.178	NaN

V. SEASONAL EFFECTS

Previous researchers modelled the environmental effects on microwave propagation separately, including the effects of rain [31], [32], snow [33], [34] and vegetation [35], [36], [37]. These models were developed using data in controlled environments where the signal path is in the order of several hundred meters and all parameters are known. Yet, in a real environment, the vegetation density and type and the portions of the path where the radio signal propagates through foliage or through free space are difficult to assess accurately, especially in wide deployment networks or hard-to-access areas or when the link range extends many kilometres. The effects of weather are also difficult to assess, as they depend on the rain or snow rate, the type of dust particles, the composition of the snow, and so on. Furthermore, for wide range links, the rain or snow rate is not uniform along the pathway.

Therefore, there is a need to create an easy, fast and comprehensive PL empirical model for seasonal environmental effects that last for many months. To our knowledge these effects have not been explored for the LD PL model. Consequently, the model is tuned and extended according to two groups of measurements: measurements taken in the summer, when the weather is warm and rainy and vegetation is growing, and measurements taken in the winter, when the weather is cold and leaves are falling. Other environmental effects, such as rain, snow and wind, are not considered since they are time-limited events, and their effects on the PL can be neglected for frequencies below 5.8 GHz [22]. Seasonal effects in the LD model.

The seasonal PL variations can be included in the LD model by splitting the winter and summer measurements into two groups, for the LOS and NLOS links. Next, each group is optimized according to the frequency band. Table 7 presents the extracted PL exponents. Note that they are higher during the summer due to the vegetation's effect. Furthermore, they are greater for the NLOS links than they are for the LOS links.

Fig. 8 compares the PL measurements with the LD model for the OUT region according to obstruction and frequency for the summer and winter seasons, respectively. The previously optimized model parameters for SLSJ are applied directly to the OUT region. The prediction curves still fit the measurements, and the model generalizes well.

A. SEASONAL EFFECT FOR THE LDH MODEL

The LDH model is optimized in the same manner used previously. Fig. 9 compares the predicted PL and measurements

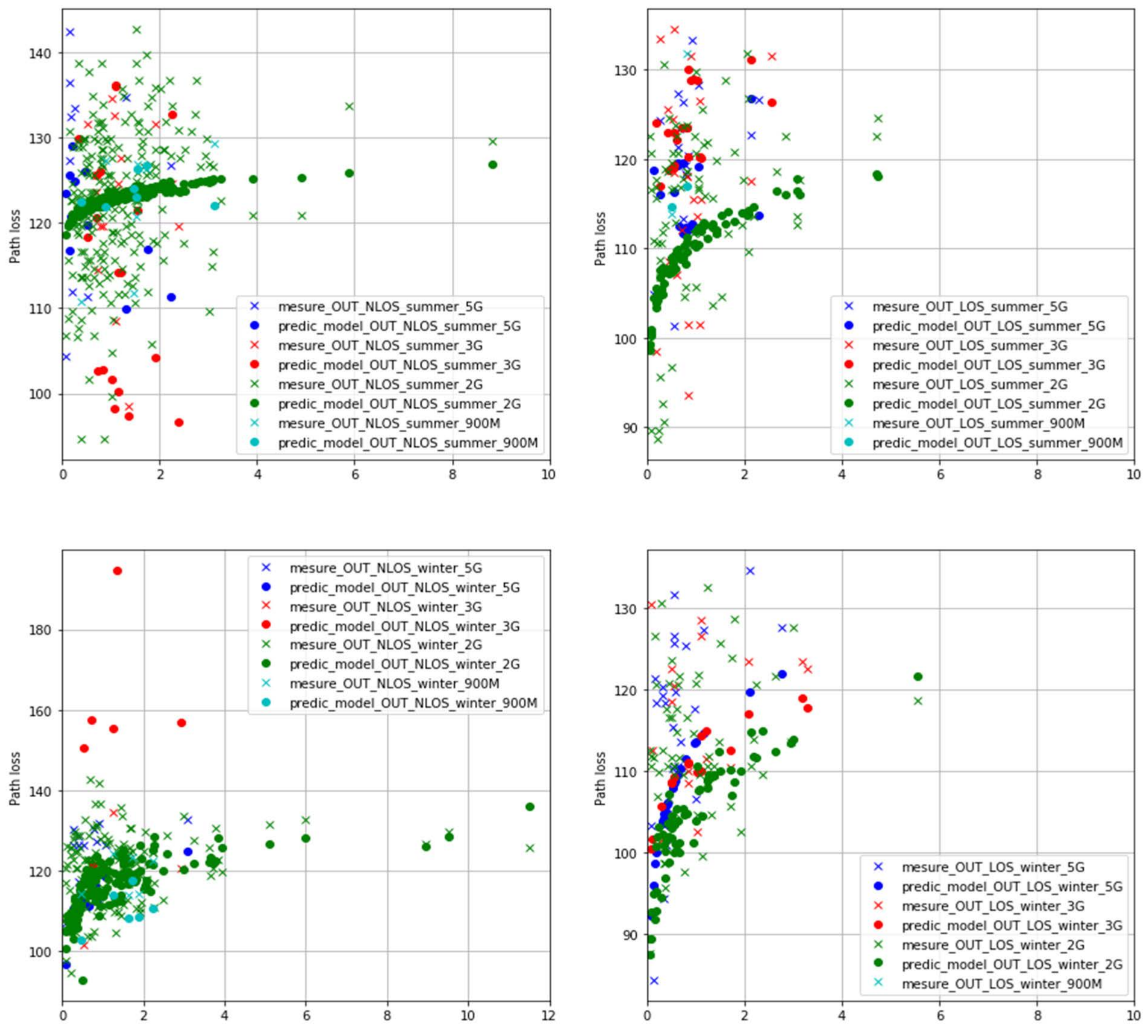

FIGURE 10. Comparison of LDHE with measurements in the OUT region according to obstruction, frequency and season.

for the OUT region. Note that the model is still accurate even though it has been optimized for a different region.

B. SEASONAL EFFECT IN LDHE MODEL

The LDHE model is optimized in the same manner that the LD and LDH models were. Fig. 10 presents the comparison between the predicted PL and measurements for OUT region. The model is still accurate when used in the OUT region.

VI. COMPARISON OF THE LD MODEL MODIFICATIONS

Table 8 summarizes the RMSEs of the various configurations of the LD model and its suggested modifications. First, the classical LD model is presented for the SLSJ and OUT regions, then the data is classified according to the LOS and NLOS links as the result of its state-of-the-art recommendations. Later, its exponents are optimized for each data classification and for its suggested modifications by considering antenna heights and elevations for the SLSJ and OUT regions. There was an important improvement, and modification had a good generalization capability compared to the classical LD.

VII. CONCLUSION

Fixed wireless networks provide easy connectivity to the internet in rural areas. Path loss models are essential for efficient planning, optimization and predicting their quality of service. Despite the diversity of existing path loss models, many reviews have confirmed the lack of accurate predictions, and their landscape is still precarious. Furthermore, research activities are focused on urban areas and mobile technologies. This paper examines the accuracy of the log distance path loss model and its possible extensions since it is quite simple to use. The target is to improve its accuracy for fixed wireless networks in the harsh propagation environments found in rural areas. For this aim, the measurements of the wide FWN of an internet service provider from two different rural regions of Canada are used. The measurements of the first region are used for design and optimization, then the second set of measurements is used for testing and validation.

The RMSE of the LD model is 27.35 dB over the whole dataset. After splitting the measurements according to the LOS and NLOS links, the RMSEs for the LD model are 16.88 and 33.24, respectively. After optimizing the path loss

TABLE 8. RMSE comparison for the various configurations of the LD model and its sugested modifications.

	LD SLSJ	LD OUT	LD (LOS, NLOS) classification	LD optimal n SLSJ	LD optimal n OUT	LDH SLSJ	LDH OUT	LDHE SLSJ	LDHE OUT
NLOS_summer_5G	28.23	25.61	33.24	11.47	20.30	11.13	22.06	15.75	14.64
NLOS_summer_3G				17.07	8.71	14.63	22.65	15.8	17.93
NLOS_summer_2G				12.82	10.27	12.75	10.41	9.6	8.03
NLOS_summer_900M				9.78	11.37	8.03	17.59	6.4	7.29
LOS_summer_5G			16.88	12.19	8.18	12.10	9.20	11.05	10.22
LOS_summer_3G				8.16	11.63	7.89	12.07	7.77	14.41
LOS_summer_2G				9.08	14.44	8.86	13.74	7.92	10.51
LOS_summer_900M				6.19	10.45	6.19	10.45	6.19	10.45
NLOS_winter_5G			33.24	9.35	11.11	9.25	10.92	9.19	12.43
NLOS_winter_3G				9.36	7.84	8.29	9.61	10.39	34.75
NLOS_winter_2G				9.27	8.89	9.11	9.31	10.19	10.16
NLOS_winter_900M				8.31	4.88	7.46	7.22	8.02	8.86
LOS_winter_5G			16.88	11.73	11.55	11.48	12.58	8.24	12.56
LOS_winter_3G				7.15	11.77	7.08	11.88	6.97	11.5
LOS_winter_2G				8.65	9.77	8.47	10.41	8.64	13.21
LOS_winter_900M				N/A	N/A	N/A	N/A	N/A	N/A

exponent and splitting the data according to region, line of sight and frequency bands, the RMSE improves considerably, as its worst value is 12.43 dB. Next, the dataset is split into many intervals according to the ascending radio signal paths. The optimal number of intervals is 10 and the corresponding RMSE is 10.1 dB. Two modifications are instituted by considering antenna heights and elevations (LDH and LDHE models). The resulting RMSEs are 10.8 and 9.8 dB, respectively. Finally, we consider seasonal variation, and the RMSE reaches 6 dB for many cases.

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