Path Loss in Urban LoRa Networks: A Large-Scale Measurement Study

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Abstract—Urban LoRa networks promise to provide a cost-efficient and scalable communication backbone for smart cities. One core challenge in rolling out and operating these networks is radio network planning, i.e., precise predictions about possible new locations and their impact on network coverage. Path loss models aid in this task, but evaluating and comparing different models requires a sufficiently large set of high-quality received packet power samples. In this paper, we report on a corresponding large-scale measurement study covering an urban area of $200\,km^2$ over a period of 230 days using sensors deployed on garbage trucks, resulting in more than 112 thousand high-quality samples for received packet power. Using this data, we compare eleven previously proposed path loss models and additionally provide new coefficients for the Log-distance model. Our results reveal that the Log-distance model and other well-known empirical models such as Okumura or Winner+ provide reasonable estimations in an urban environment, and terrain based models such as ITM or ITWOM have no advantages. In addition, we derive estimations for the needed sample size in similar measurement campaigns. To stimulate further research in this direction, we make all our data publicly available.

Index Terms—Low-Power Wide Area Network (LP-WAN); LoRa; LoRaWAN; Path Loss; Measurement; Urban;

I. INTRODUCTION

With smart cities moving towards reality, the possibility to connect and gather data from various assets enables municipalities and their associated utility companies to handle more complex tasks efficiently and effectively [1]. For example, a timely and fine-grained collection of electricity, water, or gas consumption is imperative to further improve and control supply. Likewise, a well planed smart city provides real benefits for its residents, ranging from detecting nearly full trashcans to identifying public green areas which need irrigation.

The most fundamental requirement for a smart city is a communication network connecting assets and things. Wireless communication technologies are widely preferred due to (i) the lack of wired communication paths (i.e., copper or fiber) and (ii) their cost-effectiveness and better scalability. LoRaWAN is becoming a popular choice for smart city networks due to its long-lasting battery power devices, large cell sizes, usage of a license-exempt band and therefore independence from life-cycles of Mobile Network Operators (MNOs), and possible reduction of costs [2], [3]. However, for municipalities, setting up and operating such networks is challenging due to a lack of expertise and experience. In particular, we identify the following issues: 1) insufficient protection of devices and transmissions against tampering and misuse, 2) difficulties

of transitioning from well-functioning individual projects to professionalized mass roll-out with automated commissioning and management, and 3) non-optimal radio network planning.

In this work, we specifically address the issue of non-optimal radio network planning for LoRa networks. Specifically, our goal is to aid precise prediction about possible new locations and their impact on network coverage. While MNOs have developed a broad knowledge of path loss (PL) models and can therefore predict coverage of their cellular technologies, this knowledge is often not public domain and in particular not available to municipalities. To address this issue, we cooperated with the administration of a large city and associated utility companies to conduct a large-scale city-wide measurement study and evaluated several PL models for their suitability for LoRa networks. Our contributions are:

1) We survey related work on measuring LoRa networks and PL models to derive the foundation and motivation for our measurement campaign (Section II).
2) We design and perform a large-scale city-wide LoRa measurement study in the city of Bonn, Germany. We gathered more than 112.000 samples over a $200\,km^2$ urban environment using 9 different LoRa Gateways (GWs) and our own sensors deployed on 4 garbage trucks during a period of 230 days (Section III), exceeding the scale of previous work in various dimensions.
3) We show that the Log-distance model and other well-known empirical models such as Okumura or Winner+ provide reasonable estimations in an urban environment, while terrain-based models such as ITM or ITWOM have no advantage even with LiDAR terrain data (Section IV).
4) We evaluate the progression of the Log-distance model coefficients and show a noticeable influence of including long-distance links, while sample sizes of above 20 thousand are needed for reliable conclusions (Section IV).

To enable reproducibility of our results and stimulate further research, we have made all developments (i.e., schematics and software of the sensor, implementation of PL models) and data (i.e., gathered samples) publicly available [4].

II. CAMPAIGNS AND PATH LOSS MODELS

Path loss (PL) models are an important asset for radio network planning, e.g., when making prediction about possible new locations and their impact on network coverage. To identify open issues and derive important design decisions for our own campaign, we briefly highlight the most important

TABLE I
OVERVIEW OF RELATED WORK: PREVIOUS MEASUREMENT CAMPAIGNS AND THE EVALUATED PL MODELS

Campaign						Path loss models														
						Log-distance				Empirical models									Terrain	
Paper	Year	Urban	Sub-Urban	Rural	Samples	FSPL	[5]	[6]	[7]	[8]	ITU-A	ITU-R	Winner+	3GPP	Okumura	COST	Egli	EC33	ITM	ITWOM
[5]	2015	✓			7012	✓	✓													
[6]	2017	✓			546	✓	✓	✓						✓	✓	✓	✓			
[9]	2018	✓	✓	✓	N/A										✓					
[10]	2018		✓	✓	7564	✓	✓	✓											✓	
[11]	2018	✓	✓		<600	✓														
[8]	2019	✓	✓	✓	7000	✓						✓			✓	✓	✓			
[12]	2019	✓			N/A										✓				✓	✓
[7]	2020	✓	✓	✓	38,146		✓		✓						✓	✓				
[13]	2020	✓			N/A						✓				✓	✓				
This	2021	✓			112,404	✓	✓	✓	✓	✓			✓		✓	✓	✓	✓	✓	✓

FSPL=Free Space Path Loss; [5]–[7]=Log-distance model [14]; ITU-A=ITU Advanced (UMa NLOS) [14], [15]; ITU-R=ITU-R M.1225 [14], [16]; Winner+=Winner+(UMa NLOS) [17]; 3GPP=3GPP Spatial (Urban Macro) [14], [18]; Okumura=Okumura Hata [14]; COST=COST231/Cost Hata [14]; Egli=Egli Model [19]; ECC33=ECC33 (ITU-R P.529) [20]; ITM=Longley Rice Model [21]; ITWOM=Longley-Rice and ITU-P.1546 Combined [22]

aspects of previous work. We apply a taxonomy to previously evaluated PL models and show that individual campaigns only addressed a subset of these possible models. In addition, we discuss certain aspects of previous campaigns such as sample size, post-processing of samples, and lack of verification of GPS and Received Packet Power (RPP) values.

We survey previous work on real-world measurement campaigns and an associated evaluation of different PL models for LoRa networks operating at ≈ 868 MHz. Our comparison in Table I shows numerous models (14) which have been evaluated in different measurement campaigns and environments (urban, suburban, or rural). In this work, we apply a taxonomy of four different groups to categorize PL models. A complete description of all different PL model is out of scope, however, below Table I, we provide references to all models.

The first group consists of the well-known *Free-Space Path Loss (FSPL)* model [14], which is often used as a baseline [5]–[13]. The second group consist of the *Log-distance path loss (LDPL)* model [14] (one-slop model), defined as

$$PL(d)[dB] = 10 \cdot n \cdot log_{10}(\frac{d}{d_0}) + PL_{d0} + \chi_\sigma \quad (1)$$

In this simple model, the parameters are derived from measured samples using a curve fitting method [14]. The parameter n accounts for the slope, PL_{d0} is the intercept and χ_σ is a zero-mean Gaussian random variable to account for the shadow fading. Based on their individual measurements campaigns, the authors in [5]–[8] derived different values for these parameters. For example, for the city of Oulu (Finland), the authors determined $n = 2.65$ and $PL_{d0} = 132.25$ [5]. In [8], different antenna heights of the sensor are considered as an additional parameter to the LDPL model and [7] extends this model to a dual slope model.

The third group in our taxonomy are *common empirical* PL models, known from other wireless systems operating at similar frequency bands and environments. While these models are also based on extrapolated measurement data, they typically include additional factors such as the height of the GW and sensor or corrections factors for different environments. Prominent choices are the Okumura Hata [6]–[8], [12]–[14] and the Cost Hata [7], [12]–[14] model.

The last group consists of models which need *terrain* profiles, i.e., the ITM (Longley Rice Model [21]) model and its successor the ITWOM (Longley-Rice and ITU-P.1546 combined [22]) model. Terrain profiles provide the possibility to include basic estimations for diffraction on obstacles along the communication path. Only a small subset of previous work includes these groups of models, likely, due to the increased complexity resulting from topographic data.

When comparing previous measurements campaigns, we find that these have been conducted in different *environments*, with a strong focus to urban environments due to potential applications for smart cities and a general higher asset density. Furthermore, one important characteristic when comparing different measurement studies is the *sample size* (i.e., the quantity of unique RPP measurements). Sample sizes in previous work are rather small [5], ranging from 546 [6] to 38,146 [7], though some campaigns do not explicit report sample sizes [9], [12], [13]. Obtaining samples is time-consuming due to the relative low throughput (kb/s) and regulatory restrictions: To measure samples for the maximum possible range, a Spreading Factor (SF) (the modulation of LoRa) of 12 is needed. However, even for very small payloads (e.g., GPS coordinates) only a few transmissions per hour (below 10) are allowed [23].

One important aspect of measurement campaigns is the post-processing of measurement samples [7]. Previous work argues, that a weighted fitting of samples is needed "to avoid that distances with a high number of samples have an excessive impact on the fitting" [7]. However, to the best of knowledge, previous work lacks further important discussions regarding post-processing: First, the accuracy of GPS coordinates is important especially for short distances below 1 km. Second, when using Commercial Off-the-Shelf (COTS) LoRa modems, the correctness of the reported RPP values should be validated as it directly influences results.

Motivation for this work. Based on our discussion of related work, we identify the following shortcomings that motivate our work: 1) Previous work relied on a sample size in the order of tens of thousands. However, it is unclear if this is sufficient for statistically meaningful results [5]. 2) Neither data (i.e., raw measurement samples) nor implementations of PL models
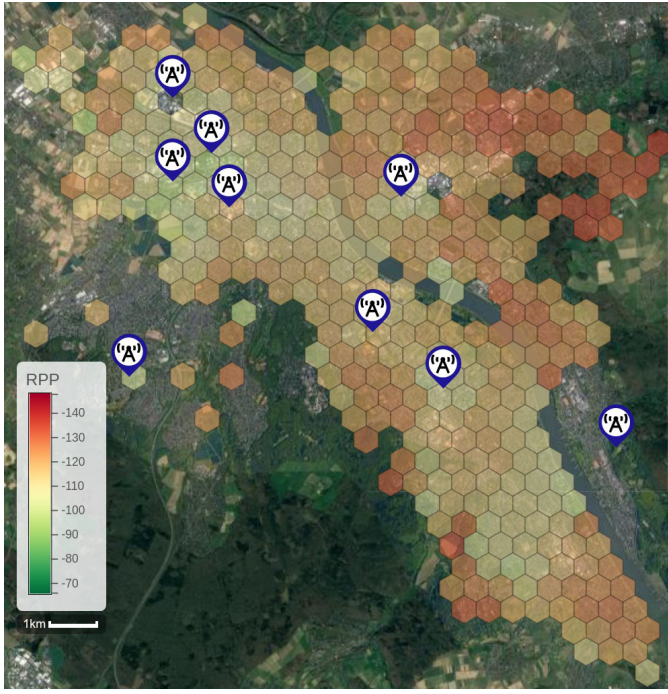
Fig. 1. Location of the GWs in the city of Bonn.

have been made available alongside previous publications. It is thus impossible to verify results or evaluate additional PL models. 3) The accuracy and correctness of GPS/RPP have not been discussed. It remains unclear if possible inaccuracies influenced results. 4) Previous publications each evaluated only a small, individual subset of PL models with divergent results. Therefore, we are unable to draw conclusions about the suitability of individual models for smart cities.

With our work, we set out to address these shortcomings and lay a foundation for further research on PL models for LoRa networks. To this end, we compare various PL models in a carefully designed large-scale measurement study.

III. DESIGN OF THE EXPERIMENT

In this section we describe the design and execution of our measurement campaign. Additional materials such as a documentation about the sensor, further validations and all measurement samples are available in public repositories [4].
Environment. The measurement campaign was conducted in the federal city of Bonn, Germany, a typical urban environment with tall- and medium-sized buildings with 330,000 inhabitants. The Rhine flows through the city and the topography is flat (cf. Fig. 1). The core components of this campaign are stationary LoRa GWs and mobile GPS sensors. Overall, 9 different LoRa GWs were distributed in the city and 4 mobile GPS sensors generated the desired samples from all over the city area. The locations of the GWs were chosen based on the availability of poles and roofs.
Hardware. Different GW models from the company Kerlink were used, each equipped with a Kerlink 3 dBi omnidirectional antenna. We measured the uplink RPP from the sensors to
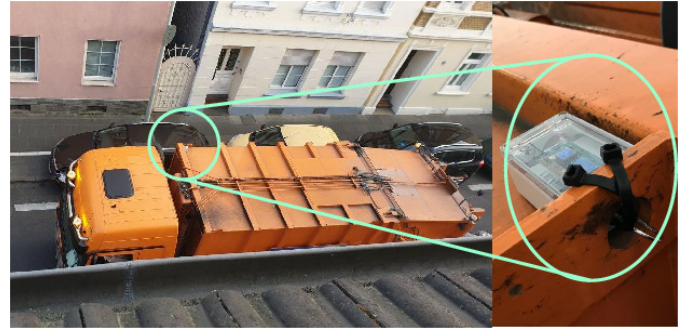

Fig. 2. Sensor mounted on garbage truck.

the GWs instead of evaluating the downlink since (i) the network was already operational with other sensors from the municipality, (ii) we wanted to avoid duty cycle limitations at the GWs, and (iii) the sensors should be as simple as possible without the need to store the gathered data.

Our most important goal was to get a significant amount of measurement samples from all parts of the city. Therefore, we needed vehicles that travel in the city over a long period of time. We contacted the city's garbage collection service, which supported us with four of their trucks. As shown in Fig. 2, our sensors were placed on the roof of these trucks and were thus part of their daily routes. After initial testing, we found that the roof of a truck is a harsh environment. Consequently, critical factors such as vibrations, water, and humidity had to be considered in the design of our sensor.

We developed our own sensor since we were unable to find a suitable one on the market. In addition, having control over hardware and software provides us with the possibility to evaluate more parameters of a sensor. Our sensor is made of a processing unit, a LoRa modem, an accelerometer, a high-quality GPS chipset, and a battery. The main processing unit of our sensor is an ESP32 Wrover B due its low power consumption. The LoRa modem is a RFM95W with 14 dBm output power, verified using a spectrum analyzer in our laboratory. The antenna is placed in the cover of the enclosure to minimize the influence of the surrounding metal. We used a Quectel L-80R as a GPS receiver module. Two replaceable EVE ER34615 (Lithium-thionyl Chloride) were used as power supply, in contrast to lithium polymer batteries also suitable for high temperature changes. A complete description of the sensor, including the schematics, is provided in [4].
Verification of the reported RPP. The RPP measured at the various GWs is the crucial parameter for our comparison of PL models. Therefore, to determine the correctness of the reported RPP values, we conducted a laboratory experiment with one of the GWs and one of our sensors before we started our measurement campaign. We connected both antenna ports using high-frequency-cables, added additional shielding, four 80 dB static attenuators, and a dynamic attenuator. Using the dynamic attenuator, we can adapt the attenuation without changing the overall experiment. We transmitted 100 packets for five different attenuation values of the dynamic attenuator and obtained the RPP at the GW.
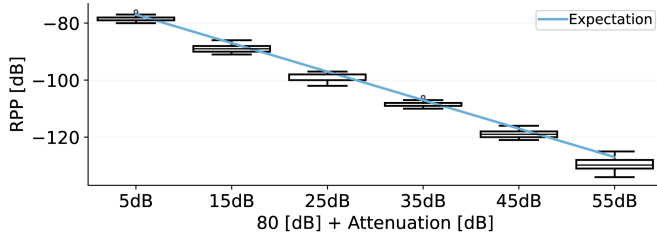
Fig. 3. Linear RPP decrease with increasing attenuation. Measured RPP values correspond well to a simple link budget calculation.
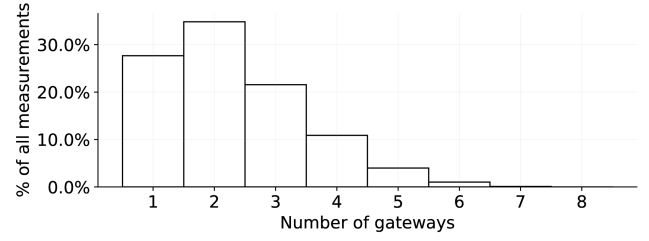

Fig. 4. Our analysis of the number of gateways receiving a certain packet shows that more than 70% of packets are received by more than one gateway.

The results shown in Fig. 3 reveal that the reported RPP decreases accordingly with an increasing attenuation, as expected. In addition, even the absolute values correspond to a simple link-budget estimation[1]. A complete documentation of our verification is provided in [4].

Measurement campaign. Finally, we mounted one sensor on each of the four garbage trucks and started the measurement campaign over a period of 230 days. If a truck (detected by the accelerometer of our sensor) moves, the GPS is switched on. As soon as the location has been determined, a LoRa packet with the determined GPS coordinates is sent to all surrounding GWs with a fixed SF of 12 (disabled Adaptive Data Rate (ADR) function) in Activation by Personalization (ABP) mode. The used bandwidth was fixed to 125 kHz at a coding rate of 4/5. Each GW which receives a packet first determines the RPP and afterwards forwards the packet (including the RPP) to our logging database. Due to our measurement setup, lost packets (i.e. due to collisions or insufficient signal strength) are not reported and can only be determined if at least one of the other GWs received the packet. Overall, our measurement campaign covered more than $200 \, \text{km}^2$ urban environment and we obtained $175,492$ individual measurement samples.

Post-processing of measurement samples. By investigating the raw measurements samples, we found that the accuracy of the GPS needs to be addressed before the evaluation of different PL models. Due to the resulting high uncertainty of the location, we removed measurements with less than 5 locked GPS satellites ($\approx 8\%$). In a second step, the remaining inaccuracy of GPS measurements was compensated by mapping locations to the nearest street using the "Open Source Routing Machine" (OSRM) service [24]. Measurements where the offset between measured and expected street was more than 20 meters apart were also filtered out ($\approx 22\%$). Furthermore, measurements with an altitude higher than the highest point of the city were sorted out ($\approx 1\%$). An indication for the resulting high accuracy of the dataset is the final filtering of all measurements with a path loss lower than the FSPL[2], which applied only to below 0.5% of all data. After post-processing, a total number of 112,372 samples remain. We did not yet evaluate the influence of a weighted fitting of

samples as proposed in [7]. A transmitted packet of a sensor was received on average by 2.3 GWs. The maximum distance between sensor and GW was almost 13 km, on average it was about 3 km.

IV. Results and Analysis

Using our gathered data, we performed various analyses, including important insights for the network operator, a curve-fitting of the Log-distance path loss (LDPL) model and the progression of the coefficients, the comparison of various previously proposed models (cf. Table I), and an estimation for the needed sample population in such measurement campaigns.

General insights. Important for the municipality is a general assessment of the network quality. As visualized in Fig. 4, around 72% of all packets were received by at least two GWs, showing good coverage of the city and redundancy of infrastructure.

Considering the strongest received RPP among multiple GWs from a single packet, 80% of these packets could have been transmitted with the best modulation (SF 7). This would drastically improve scalability when considering techniques such as ADR [23]. However, this would also decrease the amount of GWs which can decode a packet and therefore reduce the redundancy observed in Fig. 4. This is a trade-off which needs further investigation.

Log-distance path loss model in the city of Bonn. Similar to previous work [5]–[7], we use the LDPL model (described in Equation 1) to provide an empirical representation of our measurement campaign by fitting our samples to this model. Before the fitting, all samples were grouped by distance with
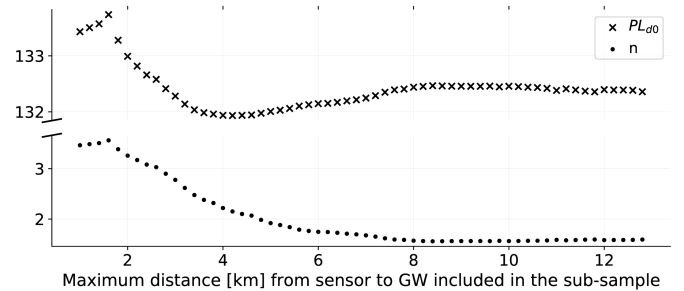

Fig. 5. Progression of the Log-distance path loss model parameters with different maximum GW distances in the sub-sample. Including long-distance measurements noticeably influences the exponent.
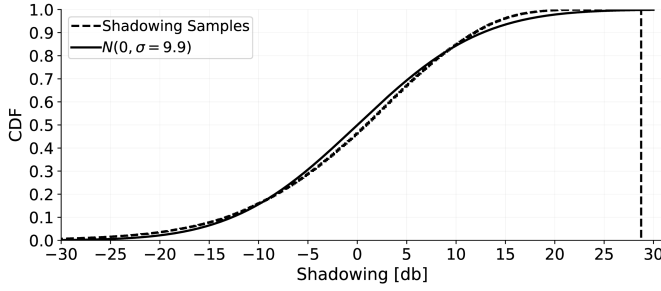
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[1]Output power - static cable/connector loss - static attenuation - dynamic attenuation = RPP $\equiv$ 14 dBm - 6 dB - 80 dB - x dB = RPP.

[2]Physically impossible and therefore directly related to erroneous locations.

Fig. 6. ECDF due to shadowing. χ_σ in Eq. 1. The distribution follows a normal distribution with zero mean and a standard deviation of $\sigma = 9.9$.

an accuracy of $10\,\mathrm{m}$ and the mean was taken for each group. The fitting yields an exponent of $n = 1.58$ and a reference loss of $PL_{1km} = 132.41$. The low value for the exponent (compared to [5]–[7]) reflects the varying topography of Bonn and in particular the long-distance measurements over several kilometers. The influence of these long-distance measurements is additionally investigated in Fig. 5. This Figure visualizes the parameters of the LDPL model for different sub-samples of our campaign. When only short distances are included in a sub-sample, shadowing of buildings has a noticeable impact (high n). If additionally long-distance measurements are considered, the exponent decreases and finally settles at ≈ 1.6. This reveals that the LDPL model highly depends on the maximum distance of measurements samples used for the fitting process. Therefore, researchers should always check the underlying link-distances used to circumvent using a LDPL model out-of bounds.

The shadowing distribution is important to assess the variance at uniform distances. Fig. 6 plots the Empirical Cumulative Distribution Function (ECDF) of the shadow fading samples and shows a well-fitting normal distribution with zero mean and a standard deviation of $\sigma = 9.9$. This reflects the heterogeneity between obstructions and reflections due to urban development and sub-urban topology.

Comparing models and real-world measurements. Using our large-scale measurements, we analyze the applicability of different PL models (cf. Section II) in our urban scenario. To this end, each model was parameterized with all necessary information, such as antenna heights, climate factors, or building density. In addition, for the terrain models (ITM and ITWOM), a digital elevation model (DEM) was build based on public available precise (accuracy $< 1\,\mathrm{m}$) LiDAR data [25]. To the best of our knowledge, this is the first time such precise topography data has used been to evaluate urban LoRa networks. For most calculations, we relied on `Signal Server` [26] and implemented the remaining ones by our own. Our parametrization of `Signal Server` and our implementations are available at [4]. All models produce an estimate of the PL from the different GWs to the locations of our mobile sensors. The estimated PL is afterwards included in a link budget to compare these estimates to the measured samples. The prediction error by a model m for a sample s, is given by the difference between the measured and predicted

TABLE II
RMSE FOR DIFFERENT PATH LOSS MODELS VS. OUR DATA-SET.

	Baseline and Log-distance models				
	FSPL	Oulu [5]	Dortmund [6]	Ghent [7]	This work
RMSE [dBm]	40.85	10.17	11.07	31.05	9.9
	Empirical models				
	Beirut [8]	Winner+	Okumura	COST	Egli	EC33
RMSE [dBm]	16.38	12.11	10.92	12.51	23.25	25.24
	Terrain models				
	ITM	ITWOM			
RMSE [dBm]	23.25	21.81			

RPP: $\epsilon_{m,s} = RPP_{measured} - RPP_{predicted}$. To quantify the performance of the models, we used the Root Mean Square Error (RMSE).

Table II shows the RMSE when applying previous proposed PL models to our measurements. The best performing models achieve an RMSE of $10\,\mathrm{dBm}$, making them suitable for real-world network planing purposes. Especially the LDPL models provide good predictions. An exception is the LDPL model from Ghent [7] which provides the worst prediction of all models for our dataset. For the group of empirical models, Winner+ and Cost-Hata have low error rates as well. This is expected, as they are all based on real-world measurements in urban environments. Interestingly, the terrain-based models ITM and ITWOM performed significantly worse. Further research is needed to determine the precise reasons, however, diffractions are probably overestimated and the more dominant reflections on buildings are not taken into account [21], [22].

While the RMSE is suitable for a general quality assessment of PL models this simple metric neglects possible systematic deviations. Therefore, the next analysis shown in Fig. 7, considers deviations of the models over varying distance using the difference between measured and predicted RPP (ϵ). Here, the empirical models (Beirut [8], Okumura Hata and Winner+) show a similar trend, as they overestimate the RPP for short distances and underestimate it for longer links. The LDPL models tend to slightly underestimate the RPP. ITM and ITWOM make opposing predictions. ITM underestimate the RPP whereas ITWOM overestimate it and both show a high variance due to the inclusion of different diffraction situations. The practical interpretation of these results is highly application dependent, as it is difficult to know in advance whether overestimates or underestimates are more harmful.

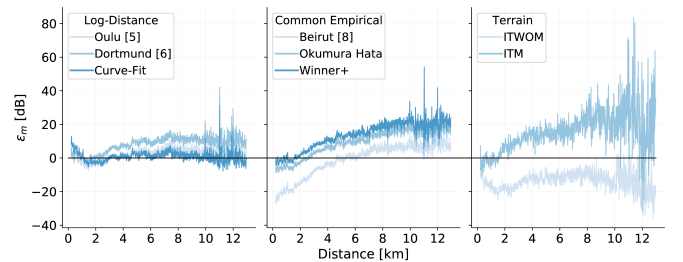In our measurement, we collected a significant number of

Fig. 7. Difference between measured and predicted RPP for varying distance. Overestimation of RPP below and underestimation of RPP above the abscissa.
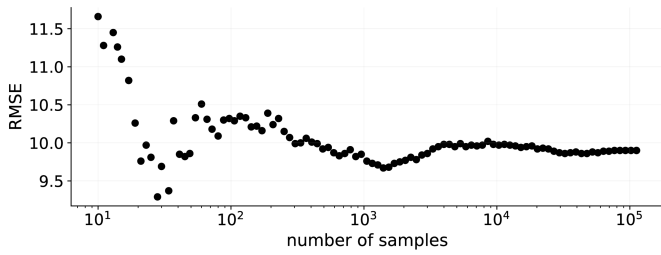
Fig. 8. Progression of the RMSE depending on the number of samples included in the fitting of our Log-distance path loss model. A significant number of samples are needed before the RMSE is stable.

samples to compare the different PL models and parametrize the LDPL model with statistically meaningful data. To this end, Fig. 8 investigates the number of samples required for the curve-fitting procedure to converge, i.e., how many measurement samples are needed to derive meaningful results. Here, the samples were randomly chosen as a subset of all measurements samples. Although nearly all related work uses sample size of less than 10 thousand, approximately 20-30 thousand samples are needed before the RMSE of the LDPL model becomes stable. Especially when sample sizes below 1000 are used for fitting and comparison (cf. Table I), authors should discuss this aspect more critically.

V. Conclusion and Future Work

In this work, we have presented the design and evaluation of a large-scale measurement study to quantify the path loss in urban LoRa networks. This work exceeds previous efforts in this field in various dimensions (sample size, duration, comparison of different path loss models). We found that simple Log-distance or empirical path loss models provide good estimations in an urban environment, while more complex terrain-based models (ITM or ITWOM) do not increase prediction quality, even with precise LiDAR data. In addition, our large sample size leads to additional insights over previous work: Common empirical models overestimate the RPP for short distances and underestimate it for long distances. We show that 20-30 thousand samples are needed to conduct a reliable fitting process for the Log-distance path loss model and that long-distance links significantly influence the results. **Future work.** Our publicly available dataset [4] provides ample opportunities for further investigations: 1) As an individual packet ID is included in our dataset, phenomena such as the average packet loss can be studied. 2) We focused on PL models, which have been used in previous work. In the future, new models may emerge and an investigation of these models using our dataset should be a straight forward task. 3) By linking the RPP to the modulation (SF), a more precise conclusion on the scalability of LoRa networks in urban environments could be drawn. 4) Using alternative models which use LiDAR topography data could lead to significantly better results, with ray-tracing being one promising approach. With our work, we lay the foundation for such interesting investigations and follow-up work. By making all our data and implementations publicly available [4], we further stimulate

research on the large-scale analysis of urban LoRa networks and large area wireless sensor networks in general. Already today, our results reveal the necessity to consider a large sample size when studying different path loss models.

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