Experimental Evaluation of Empirical NB-IoT Propagation Modelling in a Deep-Indoor Scenario

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***Abstract*—Path-loss modelling in deep-indoor scenarios is a difficult task. On one hand, the theoretical formulae solely dependent on transmitter-receiver distance are too simple; on the other hand, discovering all significant factors affecting the loss of signal power in a given situation may often be infeasible. In this paper, we experimentally investigate the influence of deep-indoor features such as indoor depth, indoor distance and distance to the closest tunnel corridor and the effect on received power using NB-IoT. We describe a measurement campaign performed in a system of long underground tunnels, and we analyse linear regression models involving the engineered features. We show that the current empirical models for NB-IoT signal attenuation are inaccurate in a deep-indoor scenario. We observe that 1) indoor distance and penetration depth do not explain the signal attenuation well and increase the error of the prediction by 2-12 dB using existing models, and 2) a promising feature of average distance to the nearest corridor is identified.**

***Index Terms*—path-loss, deep-indoor, NB-IoT, signal attenuation, LIDAR, coverage**

I. INTRODUCTION

According to IoT analytics, more than a half of the enterprise Internet of Things (IoT) projects in 2018 were classified as smart city, connected industry and connected building; in such categories, asset tracking and environment monitoring are prominent use cases [1]. Applying IoT to remote monitoring, e.g. smart water metering, the main problem is to ensure reliable connectivity and optimised power consumption of the sensors placed in basements or underground tunnels. The solution must consist of an appropriate hardware design, a suitable communication technology and knowledge of signal behaviour in the deployment area, so that the service provider can guarantee seamless and economically feasible service in the customer's environment.

Cellular IoT technologies such as Narrowband IoT (NB-IoT) and LTE for Machine Type Communication (LTE-M) are tailored for long-range applications, and they are expected to dominate the market of massive IoT due to an excellent link budget, long battery lifetime and security and reliability support [2]. Both standards provide advanced power saving mode and discontinuous reception techniques to save energy, and introduce 20dB link budget improvement in comparison to Long-Term Evolution (LTE) due to higher power spectral density and message repetition schemes in uplink and downlink [3], [4]. However, NB-IoT additionally enables multiple deployment options (in-band with LTE, in the LTE guardband and standalone) and outperforms LTE-M in terms of energy efficiency in low data-rate scenarios and when radio conditions are poor [5].

Even with NB-IoT the problem of bad or no coverage in remote, hard-to-reach areas (especially underground) persists. The number of packet repetitions is dictated by the current Coverage Enhancement (CE) level, identified by the network based on the perceived radio conditions [6]. At the same time, the energy usage grows as the number of message repetitions increases [7]. In deep-indoor situations, high signal attenuation causes NB-IoT operation on CE levels corresponding to the biggest number of repetitions (up to 128 in uplink), leading to increased power consumption. Thus, understanding signal propagation and attenuation in underground environments is essential in the process of optimal sensor placement and connectivity and throughput modelling.

3rd Generation Partnership Project (3GPP) and European Telecommunications Standards Institute (ETSI) derived theoretical path-loss models covering outdoor-to-outdoor, outdoor-to-indoor and indoor-to-indoor scenarios [8], [9]. However, the assumptions regarding deep-indoor path-loss are oversimplified for some underground scenarios (see Fig. 1). Specifically, the fact that the attenuation of the signal in the aforementioned theoretical models depends solely on the distance between the transmitter and the receiver may lead to rough conclusions not reflecting other environmental factors. For that reason, investigating new features related to the communication scenario appeals promising.

A comprehensive survey on radio propagation modelling in deep-indoor propagation situations and tunnel systems can be found in [10]. The authors discuss several modelling techniques for radio propagation in tunnels hereof the use of ray-tracing and empirical models. The theoretical analysis shows that tunnel geometry have an important impact on the attenuation rate of the received power which is not taken into account by empirical models thus leading to inaccurate predictions.

In this work, we present our efforts toward better understanding of deep-indoor path loss of NB-IoT. We conducted a measurement campaign and collected radio signal strength samples from a NB-IoT device. We observed that the received

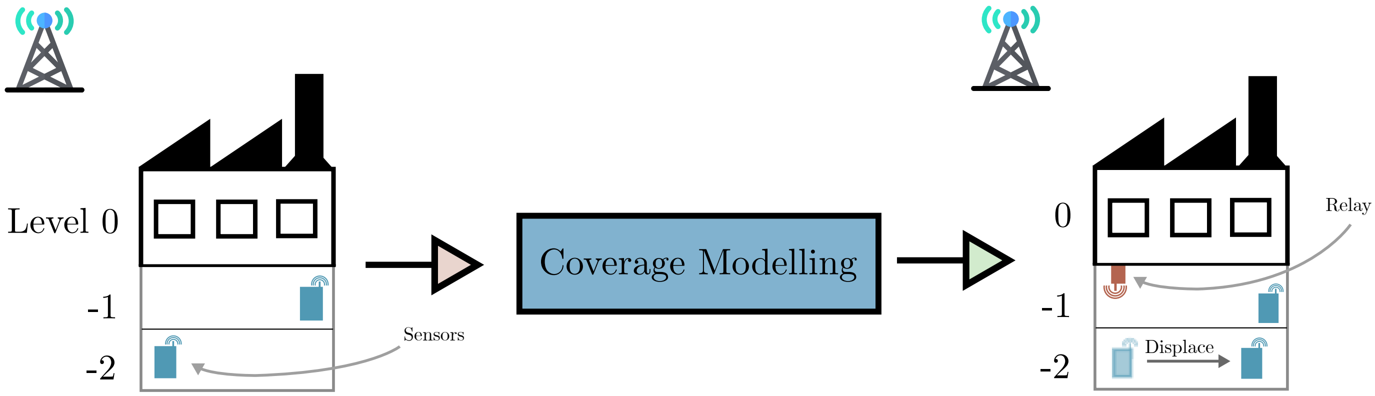


Fig. 1: Indoor deployment situations are further complicated by deep-indoor situations such as basements where coverage modelling is difficult and impractical. Current models perform well at indoor deployment situated at level 0 and above but are inaccurate at level -1 and -2. This paper presents measurements conducted at level -1 and -2.

power does not decrease with the transmitter receiver separation distance. This led us to derive more parameters - indoor depth, indoor distance and average distance to the closest corridor, and to study their significance to signal attenuation. The main contributions of the paper can be summarised as follows:

- We present a unique measurement campaign, performed in the underground tunnels and basements of the Technical University of Denmark, spanning the entirety of campus.
- We formulate the following features: indoor depth, indoor distance and average distance to the closest corridor.
- We discuss the significance of the considered parameters in modelling the path loss of NB-IoT in deep-indoor environments and open issues concerning underground deployments and coverage studies.

The remainder of this paper is organised as follows. We introduce the available path-loss models and motivate the study in Section II. The formulation of the features is explained in Section III. The description of our measurement campaign and the primary data analysis are included in Section IV. Section V contains the statistical analysis of the engineered features, and further discussion on general issues is included in Section VI. We conclude the study in Section VII.

II. Methodology

The ultimate goal of coverage modelling is to obtain realistic signal propagation behaviour, the analysis of which constitutes to more optimised real-life deployment. Apart from reflecting the field measurements faithfully, the model ought also to be generalised, in other words, applicable to more scenarios than the one accompanying model formulation. Deterministic models (e.g. Ray Tracing) take into account detailed profile of the environment, thus produce reliable predictions. However, they are computationally complex and biased towards the particular scenario. On the other hand, statistical models are simpler and more general, as they consider only limited set of variables explaining the signal attenuation, and they do not take into account the particularities of any specific environment; yet, the accuracy of the statistical models depends on the amount of available measurement data used for model derivation.

A. *Outdoor-to-Indoor path-loss*

The approach for Outdoor-To-Indoor (O2I) path-loss modelling is described in [8] and utilise a sequence of necessary steps. The path-loss is decomposed into several terms as given below:

$$\mathrm{PL}_{o2i} = \mathrm{PL}_b + \mathrm{PL}_{tw} + \mathrm{PL}_{in} + \mathcal{N}(0, \sigma_p^2) \tag{1}$$

Where, PL_b is the *basic* outdoor path-loss, PL_{tw} are losses associated with building penetration loss (constant and frequency dependent), $\mathcal{N}(0, \sigma_p^2)$ is a log-normal distribution with local variability σ_p and PL_{in} are losses dependent on the depth inside the building. However, the model is only defined for O2I scenarios with regular buildings and does not consider the indoor depth. The losses associated with the indoor distances are given as follows:

$$\mathrm{PL}_{in} = 0.5 \cdot d_{in,2d} \tag{2}$$

Where $d_{in,2d}$ is the distance indoor, e.g. the distance to the outer most wall closest to the transmitter. In a basement scenario this parameter is unspecified. The primary contribution of this paper is evaluating such indoor depth parameters for path-loss modelling.

B. *Statistical analysis*

Since the deep-indoor loss component of the official path-loss model is linear, and the main purpose of the analysis was to examine statistical significance of the features, we applied Ordinary Least Squares (OLS) regression technique [11] and compared determination coefficient R^2, Log-likelihood and Residual Mean Square Error (MSE) statistics.

III. Feature engineering

Received power of the signal decreases with increased distance as denoted by basic path-loss models, however, in the outdoor-to-deep-indoor scenario, penetrating multiple media (air, outdoor obstacles, ground, tunnel walls) makes the power-distance relationship more complex. In practice, it is difficult to know the exact characteristics of all the materials through which the wave would penetrate, or even the kind of the materials from which e.g. the underground constructions are made. Furthermore, engineering features for path-loss estimation that is capable of explaining such complex interactions is problematic due to inaccuracy of obtaining indoor positions. In this paper we obtain the indoor positions and the features using a massive and high resolution LIDAR dataset of the entire tunnel system.

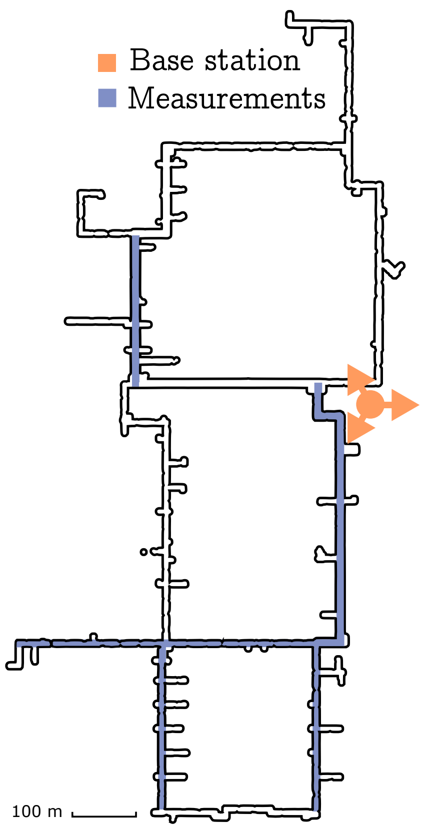


Fig. 2: Layout of tunnel system where measurements were conducted. The tunnel system is considered between level -1 and -2. The base station is placed at 30 m above top ground level.

A. Indoor positioning

Indoor positioning is a non-trivial task as common ways of obtaining positions (e.g. using Global Navigation Satellite System (GNSS) solutions) are not possible in indoor and deep-indoor situations. Several techniques for obtaining indoor positions based on radio waves are documented in literature [12] but require existing infrastructure and complex fingerprinting implementations. In this work we have access to a high resolution LIDAR dataset of the measured area (see Fig. 2). The entirety of the tunnel area is sampled in (x, y, z) coordinate points with a resolution of < 1 cm. In order to utilise such a massive dataset we used the following procedure for identifying the indoor positions. 1) each independent measurement study was composed of a starting position and an end position; 2) the start and end positions were identifying in the LIDAR dataset (point cloud) and thus the Global Positioning System (GPS) positions were extracted; 3) Using the known amount of measurements of the given corridor, in combination with the start and end position, allowed for an interpolation between the equidistant measurement points, thus giving an indoor position (with altitude information) per measurement point.

B. Defining the features

Having access to a LIDAR dataset with high resolution enabled accurate feature engineering in 3D along with accurate indoor positioning. The configuration of the NB-IoT transmitter is known, including the altitude information, GPS position and transmitter specific parameters as seen in Table. I. The accurate 3D position of the measurements in combination with the details of the transmitter allows for computation of azimuth and elevation angles for each measurement position. Additionally, the LIDAR dataset enabled more advanced features to be engineered which is the primary contribution of this paper. Using the point cloud of the LIDAR dataset, the tunnel dimensions was quantified using 3D trigonometry. This furthermore enabled the engineering of complex features such as the indoor distance (d_{in}), the penetration distance (d_{pen}), and the average distance to the nearest corridor ($d_{cor,avg}$). Both d_{in} and d_{pen} is computed in a "as-the-crow-flies" path towards the evolved Node-B (eNB) as illustrated in Fig. 3 using the elevation and azimuth angles relative to the measurement position. $d_{cor,avg}$ is computed by identifying the corridors crossing the main tunnel of the equidistant measurements using the LIDAR data. Using trigonometry, the average distance to the nearest corridor can be derived. All of the features are derived in 2D and 3D space, i.e. with and without the use of the elevation angle.

# of measurement points	895
TSMW/UE measurements per point	$1e6/10$
Operating frequency	820.5 MHz
Bandwidth	180 kHz
Noise figure (TX/RX)	5 dB/3 dB
TX power	46 dBm
Receiver antenna position	Vertical
TX/RX antenna gain	5 dBi/5.8 dBi

TABLE I: Experiment parameters

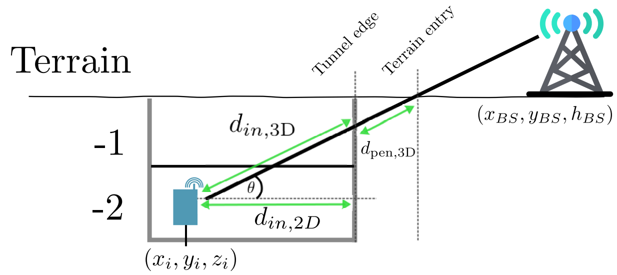


Fig. 3: Distance indoor is computed in 2D and 3D using LIDAR information of the tunnel system. The tunnel dimensions and the terrain entry point can be determined using the point cloud and the angles (azimuth and elevation) deduced from the measurement positions

The distributions of the features and their relationship with the Reference Signal Received Power (RSRP) of the NB-IoT signal are presented in Fig. 4. There is a slight and non-linear tendency that the signal attenuates with the growth of indoor depth, but in the case of indoor distance the trend is opposite. A more distinct relationship between the RSRP and $d_{cor,avg}$ is visible in Fig. 4b.

IV. Measurement campaign

We collected NB-IoT RSRP measurements and other User Equipment (UE) radio statistics from 895 measurement positions within the DTU tunnel system in Lyngby Campus. The area covered by the measurements can be seen in Fig. 2. Each of the measured corridors was divided into a set of equidistant locations (1 or 2 metres distance between two measurement positions), and the measuring equipment captured the samples at these distinct locations only, i.e. the measurements were taken stationary.

The setup consisted of a Rohde&Schwartz TSMW network tester [13], u-blox SODAQ SARA N211 NB-IoT device [14], a laptop and a gel rechargeable battery. The antennae of TMSW and the UE were fixed vertically on the trolley. At each of the measurement positions, a low-pass filter around the operating frequency was used to capture $1e6$ NB-IoT IQ samples. Parallel to this 10 measurements of UE statistics was obtained using the NB-IoT device. The mean of the measurements was taken to remove any fast-fading impairments.

A. Visualisation

A scatterplot with linear regression fit and histograms in Fig. 5 visualises the nature and mutual relation of RSRP and 3D distances between the UE and the eNB. It is possible to notice that RSRP does not depend linearly on the distance, as their distributions are clearly different; one may observe that the line representing the 3GPP model fits the experimental observations poorly. This agrees with the findings of our previous study, described in [15], but now proven over larger measurement area. Interestingly, the behaviour of RSRP with respect to the indoor distance is not linear either. Therefore, we believe that other features are needed to fully explain the complex behaviour of NB-IoT signal attenuation underground.

V. Results

A. Linear regression

Table II presents basic statistic of linear regression fit of the investigated features on RSRP. Additionally, we added a regression model employing azimuth angle ϕ and elevation angle θ. These parameters are not considered useful in path-loss modelling, but were included in the statistical analysis as a source of reference to better evaluate the indoor features.

Model M1 with 3D distance exhibits the lowest MSE (74.973) and the highest R^2 coefficient (0.285). On the other hand, M4 combining $d_{pen,3D}$ and $d_{in,2D}$ yields 0.005 R^2 and 104.335 MSE. Noteworthy, MSE of $d_{cor,avg}$ model is lower than in $d_{pen,3D}$ and $d_{in,2D}$ models by 13.934 and 12.812, respectively, and R^2 is higher by 0.131 and 0.122, respectively.

B. Indoor distance features

The O2I modelling principles as detailed in Section II-A is undefined for basement scenarios. Thus, a prediction comparison utilising the penetration distance, and the indoor distances as *indoor distances* in accordance with Eq. (2) are shown in Fig. 6. The *none* case defines the use of path loss principles for O2I scenarios using Eq. (1) but without the PL_{in} term. The remainder of the plot shows the Mean Absolute Error (MAE) prediction errors as a function of different indoor distance parameters. It is found that utilising any of the indoor distance metrics in this particular basement scenario increases the prediction error by ≈ 2 dB to ≈ 12 dB.

VI. Discussion

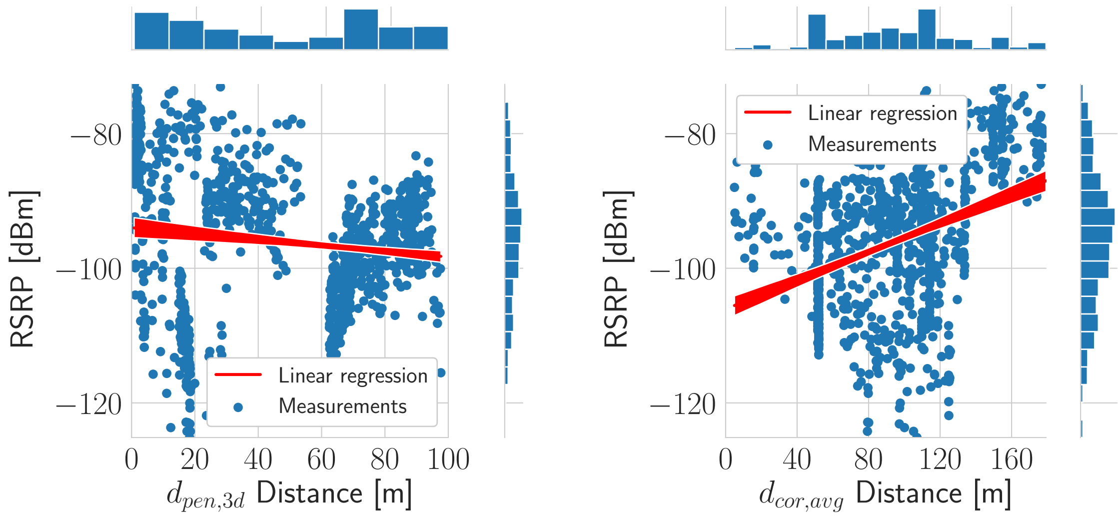
Based on Tab. II it can be observed that none of the parameters nor combinations thereof perform better than 3D distance between the UE and the eNB (model M1). Moreover, $d_{in,2D}$ and $d_{pen,2D}$ explain only marginal share of the RSRP variance and exhibit the highest MSE (M2-M4). On the other hand, model M5 involving $d_{avg,cor}$ feature, as well as model M7 consisting of ϕ and θ angles yield significantly better results. This indicates that indoor distance and indoor depth are not useful in deep-indoor path-loss modelling. Instead, the features related to the underground corridors (e.g. $d_{avg,cor}$) and/or other geographical phenomena represented here by model M7 should be considered.

A. Application considerations

In the former part of this paper we evaluated the engineered features in terms of statistical metrics, however, in order to

TABLE II: Summary of linear regression statistics

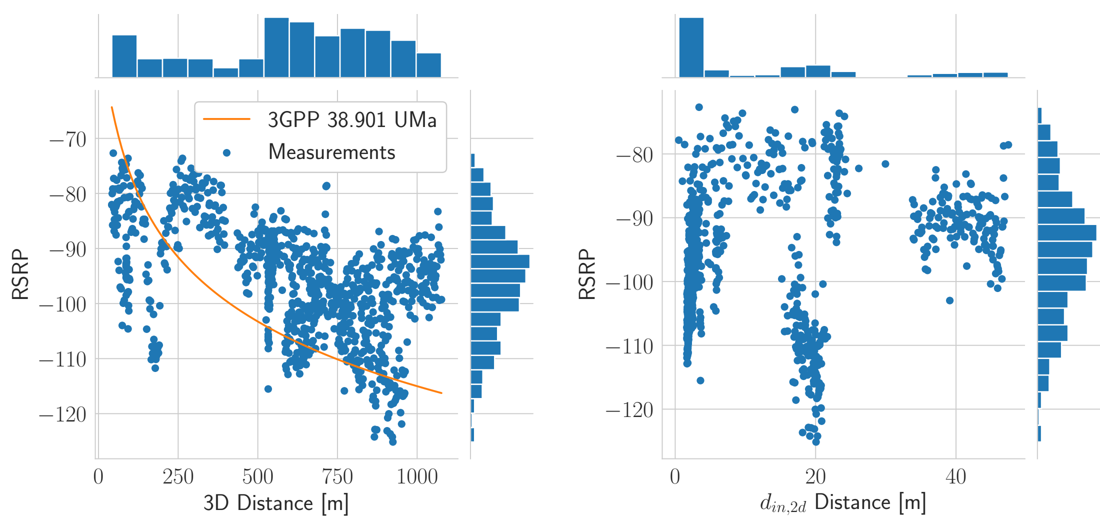
ID	Regressors	R^2	Log-likelihood	Residual MSE
M1	3D distance	0.285	-3200.9	74.973
M2	$d_{in,2D}$	0.026	-3389.1	102.098
M3	$d_{pen,3D}$	0.017	-3343.1	103.022
M4	$d_{pen,3D}$ + $d_{in,2D}$	0.005	-3348.8	104.335
M5	$d_{cor,avg}$	0.148	-3279	89.286
M6	$d_{pen,3D}$ + $d_{in,2D}$ + $d_{cor,avg}$	0.150	-3278	89.276
M7	ϕ + θ	0.173	-3265.7	86.763



(a) RSRP vs. $d_{pen,3d}$

(b) RSRP vs. $d_{cor,avg}$

Fig. 4: The relationship between RSRP and the engineered features.



(a) RSRP wrt. 3D distance vs. 3GPP path-loss model

(b) RSRP vs. $d_{in,2d}$

Fig. 5: Comparison between the observed power-distance relationship and the theoretical 3GPP model.

apply the features in real-life NB-IoT scenarios, such as smart metering or underground monitoring, the following aspects need to be considered.

1) Indoor positioning problem: Computing indoor depth and indoor distance can only be done knowing the precise location of the UE and the eNB. In our case, the availability of LIDAR point cloud was essential, as it enabled to deduce the measurement points with ca. 50 cm precision. Albeit, one certainly cannot rely on such data in an arbitrary deep-indoor area, and the fact that global localisation systems, such as GPS or GNSS are unreachable underground means that knowing where the device resides can be difficult.

2) Significance of other environmental features: Even though the results presented in Section V-A exhibit some correlation between the indoor parameters and the RSRP, a stronger relationship comes from ϕ and θ angles, which point at other features describing the measurement area and not being directly associated with indoor penetration. It is enough to mention the following: the footprint of the buildings, the size and structure of tunnel corridors and ventilation ducts or thickness of the entry doors. Moreover, the presence of machines, pipes or solid structures inside the considered underground area may also influence the coverage situation significantly. Last, but not least, one must not forget the impact

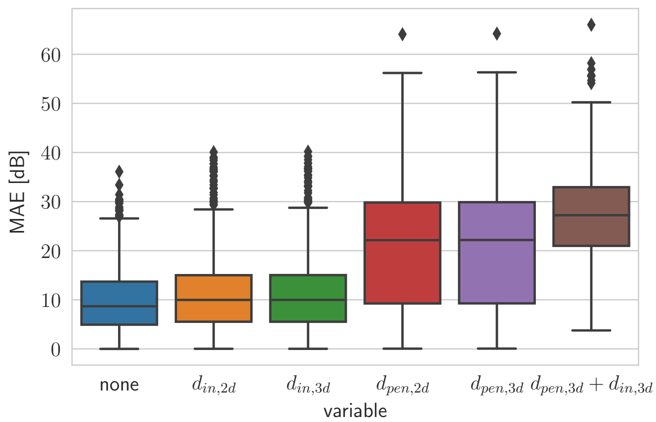


Fig. 6: MAE of utilising different indoor distance and penetration depth features in Eq. (2)

of above-ground buildings and other obstacles on power losses, even deep-indoor. Evaluating the aforementioned features is out of scope of this paper.

3) Feasibility: Examining Table II one may put in question the sense of finding indoor depth/distance features to apply them as signal power regressors; the MSE is considerably higher than in the case of total 3D distance, which is easier to compute knowing the locations of the transmitter and the receiver. Furthermore, the features alone explain less than 3% variance, which may lead to a fundamental question: should one rely on indoor depth and indoor distance in coverage prediction, or would it be more convenient to conduct trial-and-error tests instead?

As a matter of fact, not only path-loss and coverage modelling plays an important role in deep-indoor IoT service deployment planning. For instance, it is essential to provide all the devices for energy, either in a form of batteries (then device accessibility and possibility of battery replace is a key) or, possibly, with the use of locally deployed electrical installation. Moreover, in industrial scenarios, the presence of other devices or machinery might potentially cause interference.

Since we observed a significant share of variance explained by the elevation and bearing angles, we conclude that in underground scenarios the complex behaviour of signal attenuation is primarily caused by geographical parameters of the environment not explained by the features. Discovering, engineering and analysing features has been left for future work. T

VII. Conclusions

In this paper we present a measurement campaign conducted in an underground tunnel system. With the aid of LIDAR point cloud data of the tunnels, we deduced the precise locations of the measurement points and, besides 3D distance, we derived 3 more parameters: indoor depth, indoor distance and average distance to the closest corridor. A basic statistical analysis of the linear regression models revealed that indoor distance features (indoor depth and indoor distance) are not explanatory and alone cannot constitute a good approximator for margin budgets in deep indoor situations. Additionally, it is shown that current empirical models offer poor prediction performance using such indoor distance metrics. Instead, features unrelated to indoor distance (such as the average distance to the closest corridor) represent stronger correlation to the signal attenuation and should be further investigated for use in empirical path loss models.

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