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Comparison of Empirical and Ray-tracing Models for Mobile Communication Systems at 2.6 GHz

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***Abstract*—Accurate channel models for predicting received power under slow fading impairments are essential for planning 5G solutions due to the increased range of possible transmission frequencies. The densification of base stations will pose an increased number of complex coverage and capacity situations where flexible and computational simple channel models are essential. In this paper, we study state-of-the-art empirical channel models, more specifically ITU-R M.2412 and 3GPP 38.901, and their performance on experimental measurements at 2630 MHz for LTE-A reference parameters such as RSRP. A crude ray-tracing model is implemented for reference. The results show an increase in the predictive performance of approximately 4 dB at 811 MHz compared to higher frequencies of 2630 MHz.**

***Index Terms*—Radio propagation, Mobile communication, 5G mobile communication, Channel models, Path loss**

I. Introduction

The development and need for the fifth generation of mobile networks, 5G, is justified by the rapid growth and demand for wireless communication. Specifications have been put forward to deal with the need for higher data rates, quality and overall capacity. 5G, seek to take advantage of higher frequencies to accommodate the increasing demands. Due to the low penetration depth of higher frequencies, densification of base stations is imminent. This is furthermore to ensure cost/energy-efficiency while keeping the quality of service high. This is known as Heterogeneous UltraDense Network (H-UDN) and is expected to consider many different types of cells, such as macro/micro/pico, deployed in a heterogeneous and layered manner. The classic cellular architecture for coverage and capacity will likely change from using Macro base stations for both. Macro base stations will be expected to handle mainly management data and wide-area coverage while the majority of user data is to be handled by smaller cells. Due to the short inter-site distance (and thus improved radio conditions) between small cells higher frequencies such as Millimeter Wave (mmWave) are considered. mmWave and related frequencies have been subject to significant study in recent years. The work by [1] investigates and compares the recent channel models documented by 3GPP for higher frequencies.

Small cells are also anticipated to heavily make use of transmission frequencies in the range from 2-6 GHz due to their favourable propagation properties. More so, offloading to unlicensed bands in very dense urban scenarios is a foreseen need. Specifically, frequencies at 3.5 GHz are already expected released for use in LTE-A technologies and is furthermore expected for use in New Radio (NR) [2].

Channel models are considered an important element in cellular planning [3]. The accuracy of signal propagation prediction models is important both early and late in the planning process. An accurate signal propagation model needs to account for many of the complex impairments induced by the wireless channel and thus produce insight into the deployment environment. Applying ray-tracing methods on-top of constructed geographical models can offer realistic propagation maps, however, this process is in general considered time-consuming and thus expensive. Moreover, such methods are computational complex. Instead, simplified models such as stochastic/empirical models based on large measurement studies or simplified ray-tracing models have proven to be advantageous.

The purpose of this paper is to investigate and compare the performance of recent channel models for commonly used frequencies at 2 to 3 GHz. The focus is on LTE-A systems and reference signals hereof. To the best of the author's knowledge, there exists a significant need for measurement studies in the mentioned frequency range for outdoor-to-outdoor scenarios. It is worth to mention the work done by the authors in [4], as they document path loss models for a large range of frequencies (2 to 73 GHz). The measurement campaigns used in state-of-the-art models such as 3GPP 38.901 and ITU-R M.2412 can be found in [5]. It is observed that limited measurement studies at 2 to 6 GHz have been conducted for outdoor-to-outdoor Urban Macro or Micro-cell scenarios.

The paper is organised as follows. Channel modelling principles are presented in Section II. A more detailed description of the channel models can be found in related work by the authors [6]. A brief overview of Ray-tracing and Stochastic modelling techniques are given. Section III presents an overview of the latest channel models and the supported propagation scenarios. Additionally, the use of spatial correlation principles is shown. A brief comparison of the most recent channel models is given in Section III-C. Section IV details the used experimental setup and the metrics captured. Comparative results are shown in Section V for the discussed models and a ray-tracing model. Section VI and Section VII provides a discussion and conclusion respectively.

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II. Wireless channel modelling

Wireless channel models are commonly separated into two classes of definition. Stochastic and Deterministic. Stochastic channel models utilize statistics and probability captured from measurement campaigns to provide a computational efficient channel approximation. These models can also be seen as empirical models that integrate stochastic principles for worst and best case modelling. Deterministic channel models, on the other hand, seek to compute the most dominant radio waves and the resulting impairments induced by the propagation area. This means computing such effects as scattering, diffraction etc. In order to compute such effects and thus the resulting channel conditions, the models require accurate and detailed information of the propagation area.

Stochastic and deterministic models have since been trying to fill this gap of accuracy and complexity for channel modelling. A comprehensive study of wireless path loss prediction methodologies can be found in [7].

A. Deterministic models

Ray-tracing is considered the principle behind deterministic channel models. Such models require propagation specific data such as buildings and their materials, type of vegetation etc. and from this compute well-known propagation mechanics such as reflection, diffraction and scattering. This means that geographical data is required for utilizing ray-tracing in deployment scenarios. Maintaining and obtaining such geographical data is considered complex and time-consuming, however, when such data is obtained, modelling for new frequencies is trivial. [8] For these reasons, ray-tracing is commonly used for detailed propagation planning and link-level simulations, and usually cases where deployments already are present.

B. Stochastic models

Stochastic models have proven useful due to their simplicity while keeping satisfactory accuracy. These models are a tool commonly used in the planning of greenfield deployments and system evaluation since they rely on simple parameters.

These models are the product of large measurement studies (and thus empirical) in different propagation scenarios, probably most famous is Okumura-Hata and COST231.

Stochastic models offer simple single-slope log-distance expressions that are used to predict the mean path loss induced at a given distance, d from the transmitter.

Formalizing shadowing and fast fading as stochastic processes offer relatively simple models for path loss. The combined path loss can then be modelled by the following [7]

$$PL = L(d) + X_\sigma + L(t) \tag{1}$$

Where X_σ is shadowing and can be modelled as a log-normal distribution, e.g. a Gaussian random variable on the logarithmic scale with mean zero and some standard deviation σ_F [9]. $L(t)$ is fast fading and has been shown it can be represented using distributions such as the Rayleigh with a time dependency.

III. Channel model overview

Many empirical path loss models have been developed in order to deal with the use of a wide range of frequencies. For instance, the original Okumura-Hata model was extended with the Extended Okumura-Hata model to increase the range of frequencies. The increasing range of used frequencies has been a trend ever since and the development of LTE-A, and recently NR/5G, which highlights the need for many different frequencies for supplying coverage. [10]

Significant effort has been put into the study of channel models over the recent years. The aim of these models is to cover deployment scenarios for future solutions, however, since the granularity required is partly unknown the channel models aim to cover the majority of the possibilities. A few recent studies and documents should be highlighted, these can be listed as:

- METIS [11] (2015)
- 3GPP 38.901 [12] (2017)
- ITU-R M.2412 [13] (2017)

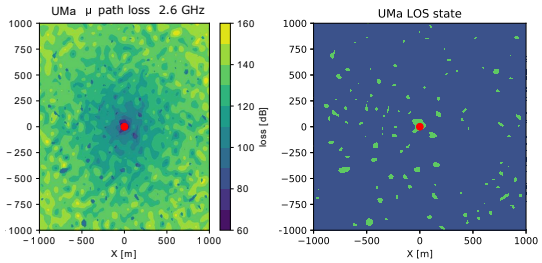
A large selection of models exists in literature, either as extensions to existing models e.g. calibration studies or original works. A more detailed comparison and overview can be found in [6]. The focus of further numerical comparisons in this paper is on 3GPP 38.901 and ITU-R M.2412.

A. 3GPP 38.901

The Technical Report (TR) 38.901 from 3GPP contains a detailed summary and overview of state of the art channel models relevant for future 5G scenarios. A large selection of the work done in the METIS project, ITU-R IMT-Advanced, WINNER+, ITU-R M.2412 has been adopted in this document. The TR contains some clear objectives to deal with future channel modelling needs. These can be summarized as 1) A large channel bandwidths, up to 10% of the centre frequency but no larger than 2 GHz. 2) UT mobility, e.g. mobility at the end of the link. 3) Large antenna arrays and 4) Spatial consistency in Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) states for large-scale and small-scale parameters. All for a wide frequency range, from 0.5-100 GHz.

The main approach for providing path loss prediction by the 3GPP 3D model consists of selecting the propagation scenario and assigning a LOS or NLOS state, as is the case with IMT-Advanced. However, unlike IMT-Advanced, the model recommends modelling spatial consistency when assigning the LOS-state. So even though probability determines the LOS-state, a spatial correlation between such states must be considered. This can, however, result in hard transitions of the channel response but can be circumvented by using an optional soft LOS state.

An example of the mean path loss with added Shadow Fading (SF) for the case of Urban Macro (UMa), that considers spatial correlation can be seen in Fig. 1a. The LOS-state, which has a large influence on the mean path loss and magnitude of shadow fading is also modelled with spatial correlation. This is seen in Fig. 1b.



(a) UMa scenario (b) UMa LOS-state

Fig. 1. Mean path loss with Gaussian distributed shadowing, σ_{SF}. Modeled according to 3GPP 38.901/IMT-2020 with spatial correlation at 2.6 GHz.

B. ITU-R M. 2412

ITU-R M. 2412 is a technical document from ITU that details guidelines for evaluation of radio interface technologies of IMT-2020. It is thus a document on how to evaluate NR solutions and is seen as an extension of IMT-Advanced.

Network layouts and configuration parameters for each of the test environments are defined in the document. For instance, Dense Urban-enhanced Mobile BroadBand (eMBB) considers three different baseline configurations where parameters such as carrier frequency, BS antenna height, transmission power, number of antenna elements and more, are defined. 3D modelling of channel propagation is considered, thus both azimuth and elevation at the transmitter and receiver antennas. Spatial consistency is furthermore added to not only Large-Scale Parameter (LSP), but also small-scale parameters, the LOS-state, indoor/outdoor state and others.

C. Comparison

The path loss models used for the 3GPP 38.901 and ITU-R M.2412 are similar and are based on the same studies, however, small differences exist. ITU-R M.2412 offers two channel models, **A** and **B**. Thus, for instance, the path loss definition and shadow fading magnitude for UMa exists in two versions, UMa_A and UMa_B. The latter is identical to the definition offered by 3GPP. This is actually the case for the entirety of model **B** defined in ITU-R M.2412. The majority of the difference between the two channel models are based on granularity. For instance, the path loss for UMa_A consists of two definitions based on frequency. One from 0.5 GHz to 6 GHz, and one from 6 GHz to 100 GHz. While UMa_B offers a single path loss model for the range of 0.5 GHz to 100 GHz.

It is of interest to investigate how the empirical path loss models, UMa_A and UMa_B perform and compare to experimental measurements. Additionally, it is of interest to compare with deterministic models such as ray-tracing that supposedly offer an improved and geographical determination of the LOS-state.

IV. Experimental Setup

The campus area of the Technical University of Denmark was selected for conducting measurements as it consists of suburban and urban characteristics such as large vegetation and condensed collections of 3 story tall buildings. Map of the area can be observed in Fig. 2.

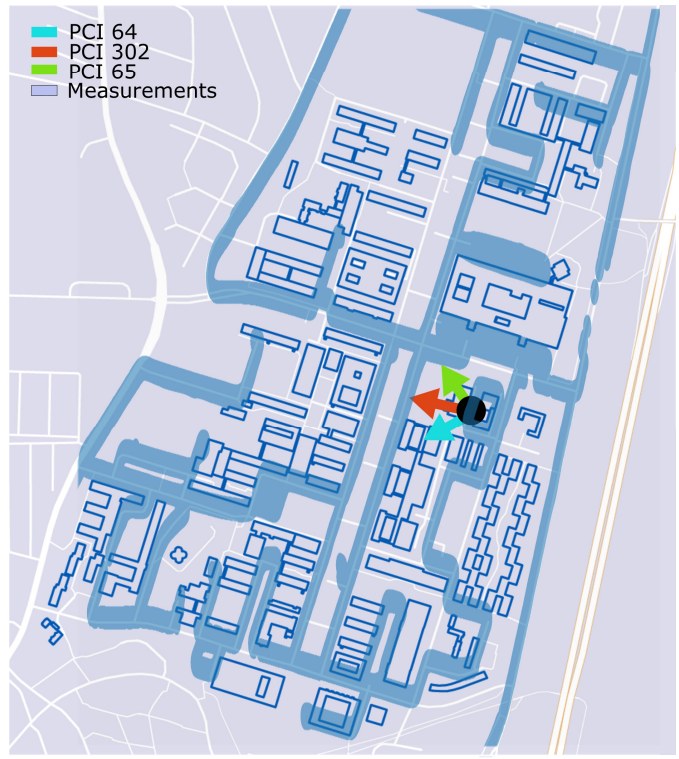


Fig. 2. Map of the Technical University of Denmark campus. Location of base stations and the route used for measurements is highlighted.

Radio measurements were obtained using a Rohde & Schwarz TSMW. A GPS module is integrated allowing for synchronization between radio measurements and GPS coordinates. The radio measurements were focused on downlink LTE-A frequencies, more specifically 811 Mhz and 2630 MHz respectively. 811 MHz was selected as a baseline for further comparisons. Three base stations transmitting from the same position, but with different configurations were used. PCI 64 and 65 are both operating at band 20 but considered two sectors of a cell site, while PCI 302 are operating at 2630 MHz and considered a single sector. 20 MHz of bandwidth is considered.

The ray-tracing model implemented is considered crude in terms of detail. LIDAR data is used to extract average building heights and standard building materials are assumed for all buildings. Thus a 3D model is constructed of the map seen in Fig. 2. Additionally, detailed and updated vegetation/clutter data is not considered in the implemented ray-tracing model. This means, for instance, the vegetation is added as larger dense areas, and not as individual trees and bushes. More specifically, the ray-tracing model was constructed using the following steps:

1) Obtained LIDAR scans of University Campus with a resolution of 5 m. [14]
2) Obtained footprints of buildings in the study area from

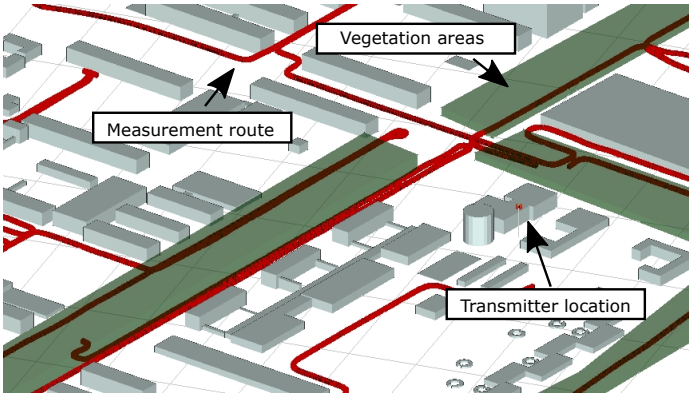


Fig. 3. Imported positions of drive-test measurements into a 3D ray-tracing model. Buildings are added using LIDAR scans, and vegetation is added using approximated geographical knowledge.

Reflections	6
Diffractions	1
Area Size	14 km^2
Number of buildings	3917
Number of faces	16563
Building material	Concrete/Brick

TABLE I
PROPERTIES OF THE RAY-TRACING MODEL IMPLEMENTED IN REMCOM.

OpenStreetMap [15]

3) Open-source software QGIS was used to extract vector shapes of buildings and their respective height.
4) Vector shapes and terrain data was added to the 3D model in the ray-tracing software. In this case, the Remcom ray-tracing solution was used. [16]
5) Approximations of materials and their permittivity were defined along with transmitter and receiver configurations.

The properties of the model are outlined in Table I. The permittivity of the building materials (Concrete/Brick) is 4.4 to 5.3 F/m. A full 3D ray-tracing approach is used, accelerated by a GPU, thus the number of faces define the overall complexity.

LTE reference signals were measured along with wideband power and Signal-to-Interference-plus-Noise Ratio (SINR) resulting in the following metrics for measurements: Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), SINR and Received Signal Strength Indicator (RSSI). The resulting dataset consists of $\sim$ 60000 data points with the above listed radio metrics. The route used is highlighted in Fig. 2.

V. RESULTS

LTE parameters such as RSRP was used to evaluate the site-specific received power. The measurements for 811 MHz can be observed in Fig. 4 while the measurements for 2630 MHz can be observed in Fig. 5. Additionally, shown in both figures, is the predicted received power provided by the UMa_A and UMa_B models given NLOS. Furthermore, the

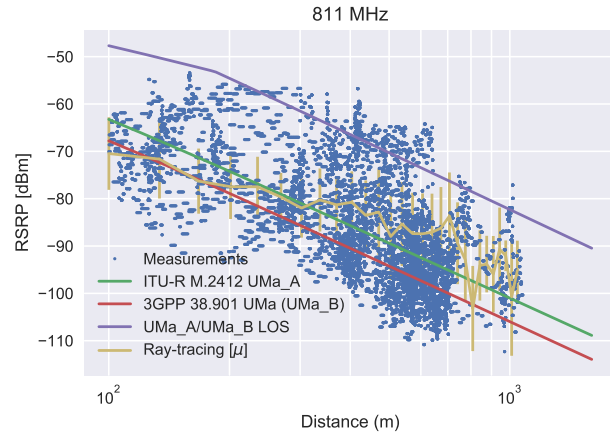


Fig. 4. RSRP at 811 MHz for measurements and the predictive RSRP provided by the channel models.

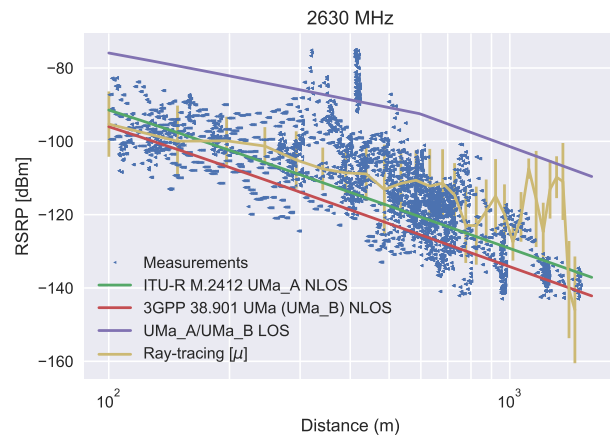
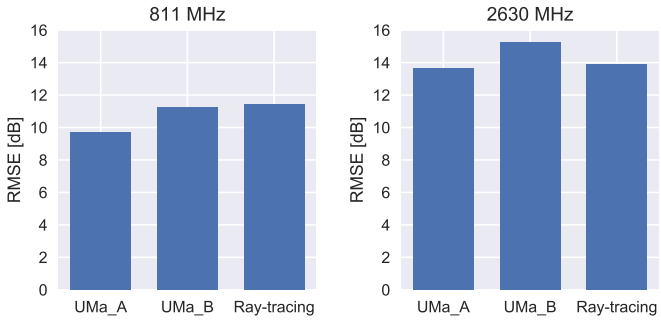


Fig. 5. RSRP at 2630 MHz for measurements and the predictive RSRP provided by the channel models.

predicted received power given a LOS-state is shown providing a reference of the best-case. The ray-tracing results are also shown, however, binned for the corresponding distance. Each bin then considers the mean and the standard deviation. A ray-tracing calculation is done for every measurement point and synchronized based on the recorded GPS position.

The model accuracy is shown in Fig. 6 in terms of Root-Mean-Squared-Error (RMSE). This is roughly equivalent to a fading margin. The best performing model thus has the lowest RMSE. The accuracy for both 811 and 2630 MHz is shown for all 3 models, thus UMa_A, UMa_B and the ray-tracing. It can be observed that the best performing model at 811 MHz is the UMa_A model, however with a similar magnitude of error and within $\sim$ 1.5 dB of each other. At 2630 MHz the error is similar for all three models, however, a slightly worse performing model can be found in UMa_B.

Comparing 811 MHz to 2630 MHz, an approximately 4 dB difference is observed between all three models. This can be seen in Fig. 6a and Fig. 6b. For instance, the error of UMa_A at 811 MHz is approximately 9.5 dB while the error at 2630 MHz is approximately 13.5 dB.



(a) 811 MHz (b) 2630 MHz

Fig. 6. Model performance at 811 MHz and 2630 MHz for empirical-based models and a crude ray-tracing model.

VI. Discussion

The increased error in model performance at 2630 MHz, compared to 811 MHz, for both the empirical-based models and the implemented ray-tracing model illustrates the impact of LOS and shadowing effects at higher frequencies. This is further illustrated by the significant clusters observed at 2630 MHz. The crude ray-tracing model offers similar error performance, but with a significant increase in data complexity and processing power. The ray-tracing model was expected to outperform the empirical models, even considering a substantial lack of detail in the model. However, as also documented by [8], ray-tracing requires much detail for accurate predictions of received power.

It is observed that the LOS-state of the models influence heavily the path loss at both 811 MHz and 2630 MHz. It can be seen that any way to determine the LOS-state at any given measurement would significantly improve the predicted error for both empirical models. This can be highlighted at 2630 MHz where a cluster is observed at a higher received power, most likely because the transmission is LOS or partially LOS. Using a stochastic approach for the LOS state and the LSP, a probability distribution of the received power can be obtained. This can assist in determining worst-case coverage and the resulting capacity, which is a useful statistic for greenfield deployment [3].

Determining the LOS-state of the propagation environment is difficult and requires a detailed model of the propagation scenario. Illustrated by the crude ray-tracing model, this is not a trivial task and requires significant knowledge and data of the geographical region. The proposed use of ray-tracing principles for LOS-state determination in combination with stochastic modelling principles, i.e. the hybrid model, is thus not a simple model. Novel and simple solutions for determining the LOS-state are of great interest for use with such empirical models. The use of deep learning for learning geographical information from simple data such as satellite images have been demonstrated in [17] and documents improved predictive performance for frequencies at 2.6 GHz.

VII. Conclusion

It is shown that empirical-based models of ITU-R M.2412, offer satisfactory performance at 811 MHz in terms of mean path loss. An increase in the predictive error of ~ 4 dB at 2630 MHz is observed for both empirical models and the ray-tracing implementation compared to that of 811 MHz. It can be observed that in any case the empirical-based models, UMa_A and UMa_B offer performance similar to that of a simple ray-tracing model. The results illustrate the need and requirement for using highly accurate and deterministic geographical information at higher frequencies in order to improve prediction accuracy.

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