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WHITE PAPER

RADIO PROPAGATION MODELLING IN THE ERA OF ARTIFICIAL INTELLIGENCE

Stefanos Bakirtzis

Ranplan Wireless, Research and Development Group, Cambridge, UK and Department of Computer Science and Technology, University of Cambridge, Cambridge, UK.

Jie Zhang

Department of Electronic and Electrical Engineering, the University of Sheffield, Sheffield, UK, and Ranplan Wireless Network Design Ltd., Cambridge, UK.



1. Introduction to Radio Propagation Models

Radio propagation modelling constitutes an indispensable component of efficient wireless network design and the successful operation of a wireless ecosystem. Indeed, obtaining accurate estimates of the electromagnetic wave propagation in an area assists the proactive wireless network design and ensures the end-users experience a high signal-to-interference-plus-noise ratio (SINR) that accommodates higher data throughput rates.

Currently, the increasing complexity of the wireless ecosystem calls for expedient and accurate propagation modelling tools that will assist the deployment of new wireless network components which will co-exist in harmony with the pre-existing ones [1]. Conventionally, either empirical or deterministic propagation models are utilized in radio frequency (RF) planning, and an acknowledged trade-off between the accuracy and the computational efficiency of these models exists [2].

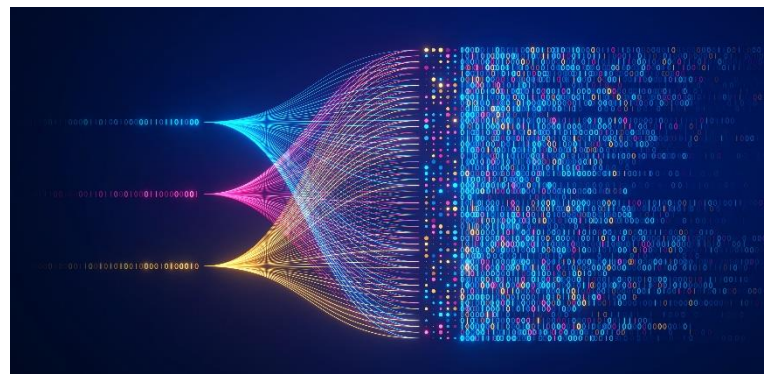
- Empirical models can promptly provide estimates of the wireless channel characteristics, but their reliability is limited.
- Deterministic propagation models can conduct realistic radio propagation simulations; however, they require large computational resources and emulation time.

To overcome this fundamental performance bottleneck, the idea of integrating existing propagation models with Machine Learning (ML) algorithms has attracted a lot of interest [3, 4]. Hence, a novel category of ML-based propagation models has emerged [4], which aspires to train ML models to learn and infer physical quantities related to radio propagation. These models can be used to expedite, calibrate and enhance existing propagation models, or even act as stand-alone propagation solvers, replicating the results of a complex deterministic solver within a few milliseconds.

Due to the swift and continuous advances in the field of computational intelligence, as well as the increasing accrual of radio propagation-related data, the prominence of ML-based propagation models in RF planning is expected to grow even more. On the grounds of that, in this white paper, we provide a brief overview of ML-based propagation models, discussing the basics of ML, conventional propagation models, and existing approaches to ML-based propagation modelling, including the contributions of Ranplan Wireless in this research direction.

2. Machine Learning in a Nutshell

Artificial intelligence aims to emulate human intelligence by conducting basic computational operations in multiple simplistic learning components. ML is a subfield of artificial intelligence which aims to process data and distil knowledge that can be exploited to carry out various tasks, and heretofore, it has been leveraged to enhance the performance of diverse applications and services of the wireless ecosystem. ML algorithms can be mainly distinguished into supervised, unsupervised, and reinforcement [5].



- **Supervised ML algorithms** attempt to establish a relationship between some input and output data. In a more formal way, this implies finding a mapping function f which transforms some input data X to some target output data Y that constitutes a quantity of interest (QoI) for a real-world problem.
- **Unsupervised ML algorithms** do not require a target output, and their goal is to identify patterns and characteristics within the input data, which consequently allows the data to separate into different clusters. More formally, unsupervised learning algorithms attempt to learn the probability distribution of the input data $p(x)$ through observation.
- **Reinforcement ML algorithms** aspire to train autonomous agents to develop optimal behavior in a trial-and-error manner and according to a specific reward and punishment policy.

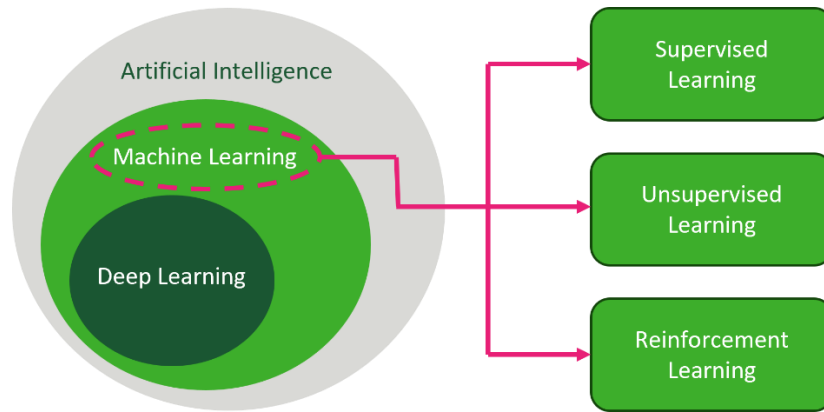


Figure 1. Categories of machine learning algorithms.

An indispensable component of supervised and unsupervised ML model is the task to process the representative data related to the underlying problem. In unsupervised learning, the ML algorithm is applied to the entire dataset in order to estimate its probability distribution, which unveils hidden patterns and properties of the dataset. In supervised learning, typically, this data is split into three different datasets: training, validation, and test dataset. The first dataset is used to estimate the learning parameters of the ML algorithm that minimize the error metric between the target data Y and the predictions of the ML model \hat{Y} . This certifies that the ML model can indeed learn from the input data and find a proper mapping function. However, unlike common optimization tasks, the goal of the ML models is to be *generalizable*, i.e., it performs well when new, previously unseen data is provided as an input; that’s why the validation and test sets are required. The validation set is used to tune hyperparameters related to the training and to select the ML model that yields the best performance. Once the training and the validation (model selection) are completed, the test dataset is utilised to prove the generalizability of the ML model and measure its performance with unknown data.

3. Legacy Radio Propagation Models

Although the nature of electromagnetic wave propagation can be captured by Maxwell’s equations, due to the wireless channel complexity, deriving an analytical solution can be impossible, even for simple propagation environments. Instead, approximate solutions to Maxwell’s equations can be derived by solving them under certain simplifying assumptions and employing numerical methods. For instance, under the geometrical optics approximation, in ray-tracing, the electromagnetic waves can be approximated as straight lines or tubes that traverse the propagation environment interacting with the objects found within their path. Alternatively, full-wave methods, such as the finite-difference time-domain (FDTD) technique, can be used to discretize Maxwell’s equation and then compute the electromagnetic fields at a given point in space and time through a set of numerical equations. Such models are called deterministic, and they are site-specific, considering the distinct particularities of the propagation environment, such as the geometry and material electromagnetic properties. Typically, the stricter the approximation used by the model, the higher the accuracy, but also the higher the computational cost. Hence, although deterministic propagation models yield accurate estimates of the wireless channel characteristics, their computational complexity makes them unappealing for large-scale network deployment or real-time applications.

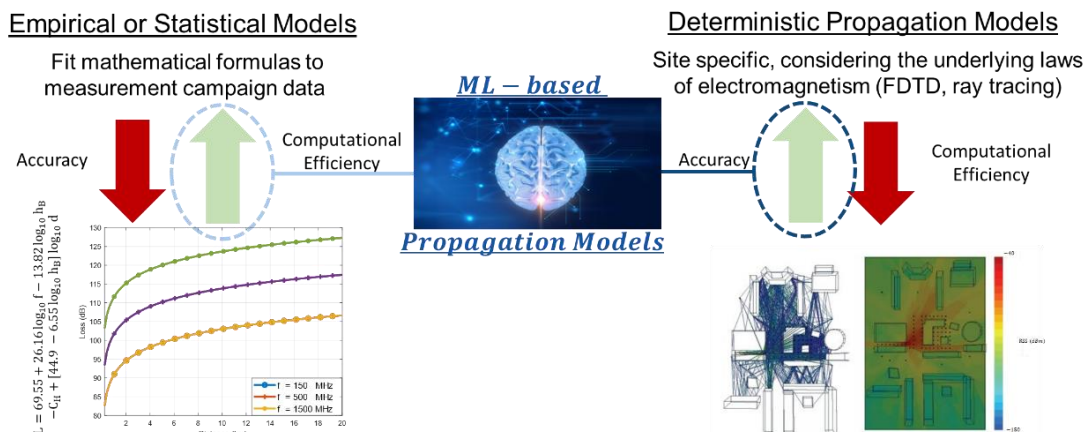


Figure 2. Performance trade-off between conventional propagation models.

A more lightweight approach would be to use empirical or statistical propagation models. These models are derived by fitting simplistic mathematical formulas to a large set of measurement campaign data, and they have been used for both outdoor and indoor propagation modelling. Consequently, due to their simplistic nature, these models are computationally efficient. However, their fidelity is limited, as they attempt to transfer statistical information from potentially uncorrelated propagation environments while using a limited amount of information. Thus, empirical models cannot precisely capture the radio wave propagation characteristics, especially as the complexity of the wireless environment increases.

4. Machine Learning-based Propagation Models

As shown in Figure 3, machine learning-based propagation models leverage a set of descriptive input features that can be processed by an ML model, agnostic to the laws of electromagnetism, in order to develop an understanding of how such features affect radio wave propagation. Eventually, the goal is to retrieve a mapping which transforms the input data features to a target QoI related to the wireless channel. Thereby, the input features ought to convey information that is intrinsically correlated to the target QoI in order to facilitate the training procedure and enhance the generalizability of the model. This information can be related to the physical environment itself or to the details and configuration of the wireless communication system. For instance, for outdoor environments, physical input features can be related to the city layout, the building height, or the terrain type, e.g., sea, forest or urban. Likewise, useful information about the indoor environment can be the wall construction materials, as well as, the respective electromagnetic parameters and reflection and transmission coefficients, the wall height, and the number of walls between the transmitter and the receiver. Parameters related to the wireless system configuration can be the operating frequency, the antenna radiation pattern and polarization, and the height of the transmitting and receiving devices.

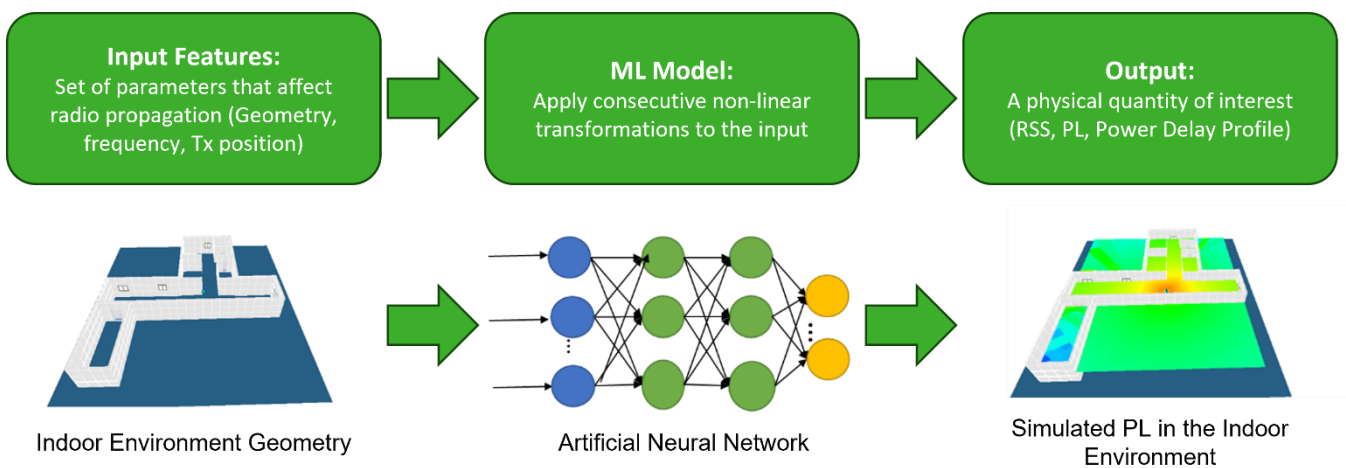


Figure 3. Pipeline of an ML-based propagation model.

The physical QoI at the output of the ML model can be related to large-scale fading, such as the pathloss and shadowing, or to small-scale fading, e.g., multipath delay or angle of arrival spread and mean. The estimates of the target QoI can be real-world measurements and/or, due to the scarcity of such data, synthetic data generated by a high-performance propagation solver. In cases where only synthetic data are used, the ML model can effectively learn to reproduce the results of the high-performance propagation solver, but in substantially reduced computational time, while simultaneous training with real and synthetic data can be used to enhance or calibrate existing propagation models. Finally, since the target outputs are continuous physical quantities, radio propagation modelling is commonly treated as a regression supervised learning problem, however, if one considers discrete values of the output QoI then it is also possible to be treated as a classification problem.

The key component of the framework presented in Figure 3 is the ML algorithm used to transform the input data into the desired output. ML algorithms, such as random forest and support vector regression (SVR), have been used to predict the signal level in mobile communication systems. For instance, in the document referenced [6] the authors used random forests, SVR and the k-Nearest Neighbours algorithm (kNN), to infer data from an unmanned aerial vehicle coverage map created using a ray-tracing simulator instead of real-world measurements. In [7] and [8], a large number of measurements collected by MNOs in different urban environments were used to train a random forest regressor receiving an input of various geographical, environmental, and wireless system-related features. In both works it was shown that the data-driven propagation model performed better compared to traditional propagation methods such as the COST 231-Hata model or a simply geospatial interpolation ordinary kriging model. Likewise, random forests and SVR were also used in [9], along with artificial neural networks (ANNs), to predict the PL, whilst considering data augmentation techniques to improve the generalizability of the model.

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