A Machine Learning based 3D Propagation Model for Intelligent Future Cellular Networks

Usama Masood, Hasan Farooq and Ali Imran
School of Electrical and Computer Engineering, University of Oklahoma, Tulsa, USA
Email: {usama.masood, hasan.farooq, ali.imran}@ou.edu

***Abstract*—In modern wireless communication systems, radio propagation modeling has always been a fundamental task in system design and performance optimization. These models are used in cellular networks and other radio systems to estimate the pathloss or the received signal strength (RSS) at the receiver or characterize the environment traversed by the signal. An accurate and agile estimation of pathloss is imperative for achieving desired optimization objectives. The state-of-the-art empirical propagation models are based on measurements in a specific environment and limited in their ability to capture idiosyncrasies of various propagation environments. To cope with this problem, ray-tracing based solutions are used in commercial planning tools, but they tend to be extremely time consuming and expensive. In this paper, we propose a Machine Learning (ML) based approach to complement the empirical or ray tracing-based models, for radio wave propagation modeling and RSS estimation. The proposed ML-based model leverages a pre-identified set of smart predictors, including transmitter parameters and the physical and geometric characteristics of the propagation environment, for estimating the RSS. These smart predictors are readily available at the network-side and need no further standardization. We have quantitatively compared the performance of several machine learning algorithms in their ability to capture the channel characteristics, even with sparse availability of training data. Our results show that Deep Neural Networks outperforms other ML techniques and provides a 25% increase in prediction accuracy as compared to state-of-the-art empirical models and a 12x decrease in prediction time as compared to ray tracing.**

***Index Terms*—Pathloss Prediction, Ray Tracing, Radio Propagation Model, Machine Learning.**

I. Introduction

Next generation of cellular networks is anticipated to see a dramatic growth in connected devices and exciting new vertical services. Hence, Self Organizing Network (SON) is considered to be the key enabler to meet the stringent performance requirements in the increasingly complicated process of planning, operating and optimizing a network. Therefore, a realistic propagation model that is more accurate than empirical propagation models, such as COST-Hata [1], Stanford University Interim [2], Standard Propagation Model (SPM) [3] and ITU-R P.452-15 [4], more computationally efficient than deterministic models such as *ray tracing* and sensitive to the variation in network parameters (e.g. tilt) and environment geography will be the cornerstone of self-organizing future cellular networks (5G and beyond). To address the constraints and limitations of traditional channel modeling methods, Artificial Intelligence (AI) and Machine Learning (ML) techniques are being considered as promising viable solutions and have been proven to be very effective for approximating arbitrary functions with hidden features. As envisioned in [5], *Artificial Intelligence* is going to be indispensable in increasingly complex cellular networks and can replace classical mathematical models with a robust data-driven model.

A. Relevant Works

Many studies are presented in the literature for pathloss prediction in a particular environment using machine learning based models. Artificial Neural Networks (ANN) have been the most commonly used pathloss prediction models, particularly in rural [6] and urban [7] environments, however the input features to the ANN model are limited to a particular environment and unable to scale to other environment settings. The authors in [8] went one step ahead and used evolutionary algorithms to find the optimal hyper-parameters of the ANN based model, but they assumed a uniformly structured simulation area, which is not the case in practical scenarios. A more recent study in [9] incorporated features based on clutter maps to differentiate between different environments, but still unable to capture the variation in coverage due to the change in geometrical structure of the propagation path. On the other hand, authors in [10] compared the performance of several supervised ML algorithms for estimating cellular networks coverage, using User Equipment (UE) measurement traces, Base Station (BS) parameters and geographical information. However, instead of modeling the pathloss or Received Signal Strength (RSS), the authors classify the observation area as a good or a bad coverage area, using a pre-defined coverage threshold.

B. Contributions

To address the limitations of aforementioned studies, we present a framework for an ML-based 3D propagation model (See Fig. 1), that is scalable and robust to the variations in the environment geography. The contributions of this paper can be summarized as follows:

- A novel set of smart predictors (features) are proposed, that can characterize the physical and geometric structure of the environment traversed by a signal in its propagation path (e.g. *indoor distance, outdoor distance, number of building penetrations in each clutter type*).
- Various machine learning algorithms are investigated in modeling the complex propagation environment especially in sparse training data scenario, and Deep Neural Network (DNN) is found to be the most optimal choice.

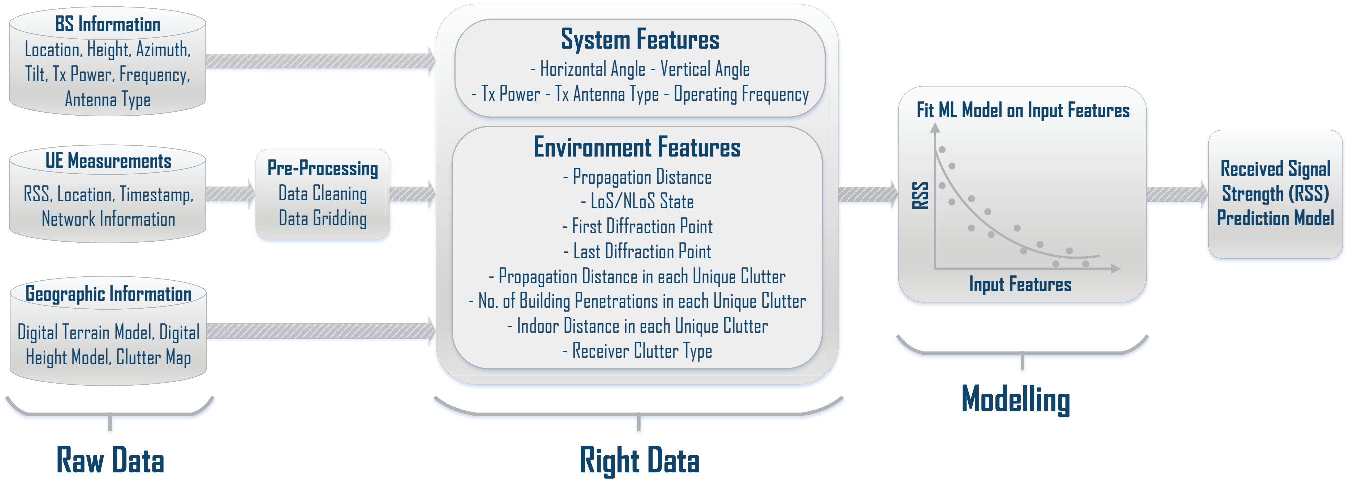


Fig. 1. Proposed Framework of an ML-Based 3D Radio Propagation Model for predicting the Received Signal Strength (RSS)

- Performance comparison of the proposed model with state-of-the-art empirical propagation models and ray-tracing approach is also provided, which shows a 25% increase in prediction accuracy as compared to empirical propagation models and 12x decrease in prediction time as compared to ray tracing.

The rest of the paper is organized as follows: Section II explains the proposed system model, starting from data collection, data pre-processing, feature engineering and a comparison of various machine learning algorithms for predicting RSS. Section III provides the performance comparison of the proposed model with traditional propagation models and finally Section IV concludes this paper.

II. System Model

The proposed framework for a ML-based 3D propagation model (Fig. 1) uses network information, UE measurement traces and geographic information of the area, pre-process them and converts them into right data [5], which is then fed to a ML model to learn the behavior of received signal strength (RSS) of a UE in a radio propagation environment.

A. Data Collection

A ray-tracing based realistic commercial planning tool is used to create a sophisticated network topology (Table I), and generate different types of raw datasets used in our proposed framework (See Fig. 2).

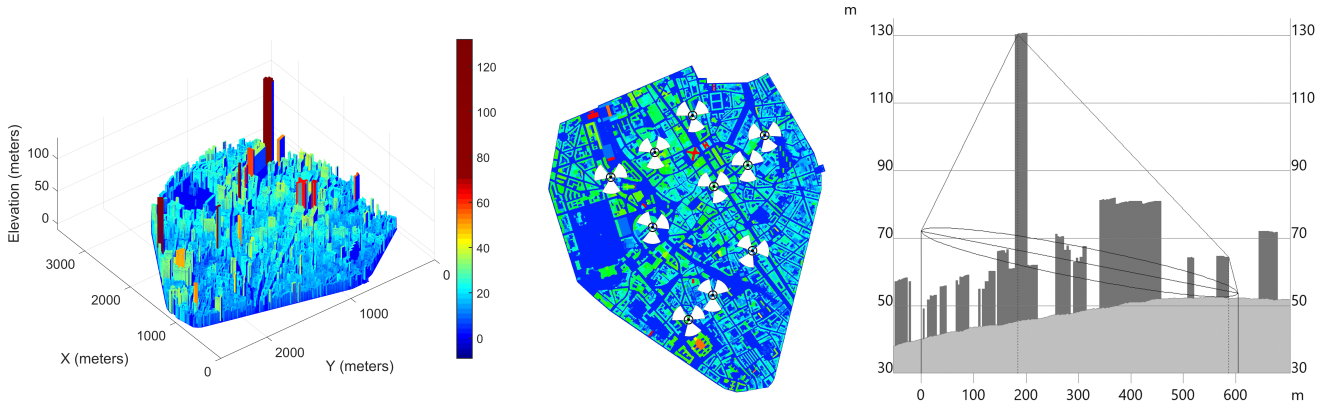
1) **BS Information***:* This dataset contains the following information of all the Base Stations (BSs) in the observation area: *Location:* Location coordinates of a BS site. Fig. 2(b) shows the position of transmitters in the simulation area. *Height:* The height of BS antenna above the ground and building (if any). *Azimuth:* Azimuth angle (in degrees) of the BS antenna, which is the direction of antenna w.r.t. North. *Tilt:* Tilt angle (in degrees) of the BS antenna, which is basically the angle below the horizontal plane. *Transmit Power:* The power of the radio signal (in dBm) when it's transmitted from the BS antenna. *Frequency:* Carrier frequency used by the BS antenna for transmission. *Antenna Type:* The type of antenna used by the BS transmitter. It is differentiated by beamwidth, antenna gain etc.

2) **Geographic Information***:* The geographical information of the propagation environment can be captured using three different types of geographical datasets. The first dataset is called *Digital Terrain Model (DTM)*, which provides the earth terrain altitude (ground height). Fig. 2(c) shows the variation in ground height in the propagation path between a BS and UE. Second dataset is called *Digital Height Model (DHM)*, which provides the building heights (above the ground) in the observation area. Fig. 2(a) shows the 3D building heights in the simulation area. The third dataset is called *Digital Land Use (DLU) Map*, which provides the clutter (or land cover) type of each grid in the observation area. These datasets are in a raster grid format, which means that the whole observation area is divided into grids (or bins), each grid containing a specific value. These geographical datasets are routinely used by mobile telecom industry for their planning and maintenance tasks, and can be acquired on demand [11].

3) **UE Measurements***:* This dataset contains the following information of all the UE's in the observation area: Received Signal Strength (RSS) from the serving BS. *Location*: Location coordinates of a UE. *Timestamp*: Time at which the UE measurement is recorded. *Network ID*: Information regarding serving BS ID, Mobile Network Code etc. The mobile operators can readily use the data from Drive Tests, Minimization of Drive Test (MDT) reports, crowdsourcing applications etc. to generate this dataset, without the need for any new standardization.

B. Data Pre-processing

UE Measurements are pre-processed by cleaning and gridding, before using them for modeling. Data cleaning is done to handle missing and corrupt values, whereas, Data Gridding is the process of mapping all UE measurements into unique



(a) 3D Elevation Map (b) 2D Elevation Map (c) Propagation Path between a BS and UE

Fig. 2. Area of Simulation showing (**a**) Building Heights (**b**) Transmitter Positions and (**c**) Vertical Propagation Path

TABLE I
NETWORK SCENARIO SETTINGS

System Parameters	Values
Cellular Layout	10 Macrocell sites
Sectors	3 sectors per BS
Simulation Area	3.80 km^2
No. of Users in Simulation Area	9755 users
User Distribution	Poisson Distribution
Path Loss Model	Ray Tracing
Geographic Information	(*1-m Resolution GeoData*) Ground Heights (DTM) + Building Heights (DHM) + Land Use Map (DLU)
Land Cover (Clutter) Types	15 different classes
BS Transmit Power	43 dBm
Antenna Gain	18.3 dBi
Horizontal Half Power Beamwidth	63^o
Vertical Half Power Beamwidth	4.7^o
Carrier Frequency	2100 MHz

spatial bins and then averaging the measurements inside each spatial bin. The advantage of data gridding is two-fold: First, it handles positioning error in the measurements, and secondly, it can offset random noise (or shadowing) from the received signal strength (RSS). As shadowing is modeled by a Gaussian Distribution with zero mean, thus averaging all measurements from the same BS, falling in a grid (e.g. 10m x 10m), will give the expected value of RSS in that grid.

C. Feature Engineering

Feature engineering is a key process in ML, that leverages domain knowledge to create features which can characterize the complex target model and greatly enhance its learning performance. In our study, several *smart predictors (features)* are identified (engineered), to better characterize the environment traversed by a signal in it's propagation path. The raw network, UE and geographic datasets, readily available to the mobile operators, are converted into right data (smart features) comprising of system as well as propagation environment features.

1) **Propagation Distance***:* This is the horizontal distance (in meters) between a UE and it's serving BS.

2) **Horizontal Angular Separation***:* This is the horizontal angular separation (in degrees) between the BS antenna boresight and the direction of Line of Sight path to the UE. This feature captures the attenuation due to horizontal antenna pattern of the BS.

3) **Vertical Angular Separation***:* This is the vertical angular separation (in degrees) between the BS antenna boresight and the direction of Line of Sight path to the UE. This feature captures the attenuation due to vertical antenna pattern of the BS.

4) **LoS / NLoS State***:* This tells if the link between BS and UE antenna is in Line of Sight (LoS) or Non Line of Sight (NLoS) state. This feature is particularly useful in wireless channels, as higher RSS is experienced by a UE which is in LoS with the BS, and vice versa.

5) **First Diffraction Point***:* This is the horizontal distance (in meters) from a BS to the first diffraction point in the propagation path between a BS and UE (See Fig. 2(c)). This features captures the significance of diffracted rays at the receiver as multiple rays from the same BS are received and the ray having highest signal strength is selected as the dominant ray.

6) **Last Diffraction Point***:* This is the horizontal distance (in meters) from a BS to the last diffraction point in the propagation path between a BS and UE (See Fig. 2(c)). This features also tries to learn the behavior of diffracted rays in the estimation of RSS.

7) **Number of Building Penetrations***:* This is the number of buildings penetrated by the signal in its direct path between a BS and UE. This feature characterizes the penetration loss (dB) experienced by the signal while crossing buildings.

8) **Indoor Distance***:* Horizontal Distance (in meters) in the direct path between a BS and UE that is passing through buildings (indoor). This feature characterizes the linear loss (dBm/m) experienced by the signal in indoor area.

9) **Outdoor Distance***:* Horizontal Distance (in meters) in the direct path between a BS and UE that is in open area (outdoor). This feature characterizes the linear loss (dBm/m) experienced by the signal in open area.

10) **Receiver Clutter Type:** It is the clutter type (or land cover type) of the receiver. (For Example: Open, Dense Buildings, Sparse Buildings, Trees, Water etc.). Each clutter type has its own effect on the signal and this feature tries to learn this behavior.

11) **Number of Building Penetrations in each Clutter Type***:* This is the number of buildings penetrated by the signal in each unique clutter in the direct path between a BS and UE. Different clutters can be different types of buildings, each having different penetration loss (dB). If our observation area consists of 15 different clutter classes, then this feature is subdivided into 15 different features, each representing the number of building penetrations in that respective clutter, whose sum equals the total number of building penetrations in the propagation path of that UE.

12) **Indoor Distance in each Clutter Type***:* Indoor Distance (in meters) covered by each unique clutter in the direct path between a BS and UE. This feature characterizes the linear loss (dBm/m) experienced by the signal in different indoor environments. Again, this feature is subdivided into the total number of clutters in the observation area, whose sum equals the total indoor distance in the propagation path of that UE.

13) **Outdoor Distance in each Clutter Type:** Outdoor Distance (in meters) covered by each unique clutter in the direct path between a BS and UE. This feature characterizes the linear loss (dBm/m) experienced by the signal in different outdoor environments. Again, this feature is subdivided into the total number of clutters in the observation area, whose sum equals the total outdoor distance in the propagation path of that UE.

D. Machine Learning Models for RSS Prediction

RSS Prediction is essentially a regression problem, where the smart features are used as inputs to the ML model, to learn the complex behavior of a signal passing through a wireless channel. Various machine learning regression algorithms are investigated for their performance comparison in predicting RSS. A brief overview and insights from each of these algorithms are also provided to make this paper self-contained. Algorithm 1 explains the process of removing shadowing from the UE measurements by gridding (averaging all measurements in a spatial bin) and then training the ML model using the computed smart features as input and the corresponding expected value of RSS as output.

1) Linear Regression: Linear Regression is a parametric model that gives a weight parameter to each feature, so that the output will be a linear function of features and weight parameters. It's not applicable to many real world problems, such as ours, as it assumes the solution to be linear and features to be mutually independent.

2) k-Nearest Neighbors: k-Nearest Neighbors (k-NN) is a non-parametric model, that can handle non-linearity. It predicts the output by exploring the neighborhood of test measurements. Output is basically the mean of k nearest data points in the training data.

3) Decision Tree: Decision Tree is a tree-based algorithm, with an inverted tree derived from independent variables, starting from a root node, where each node splits the instance space into multiple sub-spaces according to a condition over a feature, and ending at leaf nodes, where output is predicted.

Algorithm 1 Data Grdding and Model Training Algorithm

for all UE measurements **do**
    Map its location to pre-defined grids (e.g. 10m x 10m)
end for
for each unique grid **do**
    for each unique serving BS **do**
        Average out the RSS of all users to offset random shadowing effect
        Compute a feature vector of smart predictors utilizing all the raw datasets
    end for
end for
Train the Machine Learning model using all feature vectors as input and the corresponding RSS value as the output

4) Deep Neural Network: Deep Neural Network (DNN) algorithm belongs to a special class of machine learning, called *deep learning* and creates a *multi-layer perceptron (MLP)* to find the input-output associations. Its basic structure consists of an input layer, output layer and one or more hidden layers between them, each containing several neurons (or nodes). Neurons in the input layer equals the number of input features, whereas output layer consists of one neuron which holds the prediction output. Number of hidden layers and its neurons are variable, and depends on the complexity of model it is trying to learn.

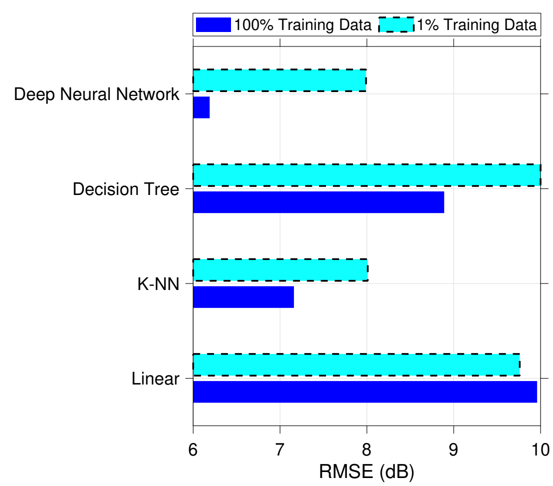


Fig. 3. Comparison of different Machine Learning Algorithms w.r.t Prediction Error and Robustness to Sparsity of Training Data, for Modeling RSS

5) **Performance Comparison***:* As shown in Fig. 3, *Deep Neural Networks (DNN)* performs the best in capturing the variance of RSS (or pathloss) in a wireless channel and only gives a prediction Root Mean Square Error (RMSE) of *6.19 dB*, as it is able to learn complex non-linear relationships due to it's deep architecture. In our DNN model, 6 hidden layers each consisting of 32 neurons provide the most optimal results, any increase or decrease in this number results in over-fitting or under-fitting on the training data respectively. *Rectified Linear Unit (ReLu)* activation function is used in the hidden layers whereas output layer uses *linear* activation function.

However, the complex non-linear nature of wireless channel renders *linear regression* method unsuitable, as it gives a very high prediction (RMSE) error of *9.96 dB*. Similarly *k-NN* and *Decision Tree* algorithms are unable to generalize well on the training data and gives a prediction error (RMSE) of *7.16 dB* and *8.89 dB* respectively.

All the models are also separately trained on only 1% of training data, to evaluate their performance in case of data sparsity, as is the case in real practical scenarios. Overall, DNN algorithm outperforms others, even with sparse training data, therefore it is used for further simulations and results.

III. Comparsion with Empirical Radio Propagation Models

We compare the performance of our proposed ML-based 3D propagation model using DNN algorithm with traditional empirical propagation models, as they are currently used in state-of-the-art commercial planning tools to characterize the propagation behavior of a radio signal in different conditions. Empirical models offer a mathematical equation to calculate the path loss at any given point from the BS, and are based on data collected in a specific scenario.

A. COST-Hata Model

It is an empirical model for pathloss calculation [1], that extends the Hata formulae [12] to frequencies upto 2 GHz and it also takes into account the topo map (DTM) between the BS and UE and morpho map (DLU) only at the receiver. The below equation is valid for urban environments with 1.5m UE height.

$$L_{path} = A_1 + A_2 * log(f) + A_3 * log(h_{BS}) + (B_1 + B_2 * log(h_{BS}) + B_3 * h_{BS}) * log(d). \quad (1)$$

Here L_{path} is the pathloss (in dB), $A_1 = 46.3$, $A_2 = 33.9$, $A_3 = -13.82$, $B_1 = 44.9$, $B_2 = -6.55$, $B_3 = 0$ are user-defined parameters, f is the carrier frequency (in MHz), h_{BS} is the height of BS and d is the propagation distance between BS and UE.
For Urban Areas:

$$L'_{path} = L_{path} - a(h_{UE}).$$

For Sub-Urban Areas:

$$L'_{path} = L_{path} - a(h_{UE}) - 2 * (log(\frac{f}{28}))^2 - 5.4.$$

For Quasi-Open Rural Areas:

$$L'_{path} = L_{path} - a(h_{UE}) - 4.78 * (log(f))^2 + 18.33 * log(f) - 35.94.$$

For Open Rural Areas:

$$L'_{path} = L_{path} - a(h_{UE}) - 4.78 * (log(f))^2 + 18.33 * log(f) - 40.94.$$

Where L'_{path} is the corrected pathloss and $a(h_{UE})$ is the correction factor for UE height different from 1.5m.
For Rural/Small Cities:

$$a(h_{UE}) = (1.1 * log(f) - 0.7) * h_{UE} - (1.56 * log(f) - 0.8).$$

For Open Rural Areas:

$$a(h_{UE}) = 3.2 * (log(11.75 * h_{UE}))^2 - 4.97.$$

B. Stanford University Iterim (SUI) Model

It is derived from the Erceg-Greenstein propagation model [13] and is valid for 1900-6000 MHz. It also takes into account the topo map (DTM). It uses the following formula:

$$L_{path} = -7366 + 26 * log(f) + 10 * a(h_{BS}) * (1 + log(d)) - a(h_{UE}), \quad (2)$$

where,
$$a(h_{BS}) = a - b * h_{BS} + \frac{c}{h_{BS}},$$
$$a(h_{UE}) = X * log\left(\frac{h_{UE}}{2}\right).$$

Here $a(h_{BS})$ and $a(h_{UE})$ are the correction factors for BS and UE antenna heights respectively, f is the operating frequency and d is the propagation distance (in km). $a = 4.6$, $b = 0.0075$, $c = 12.6$ and $X = 10.8$ are the correction constants which depend on the terrain type. [2]

C. Standard Propagation Model (SPM)

It is derived from the Hata formulae and is valid for 150-3500 MHz. It also takes into account the topo map (DTM) and morpho map (DLU) between the BS and UE. It uses the following formula:

$$L_{path} = K_1 + K_2 * log(d) + K_3 * log(h'_{BS}) + K_4 * L_{diff} + K_5 * log(d) * log(h'_{BS}) + K_6 * h'_{UE} + K_7 * log(h'_{UE}) + K_{clutter} * f(clutter). \quad (3)$$

Here $K_1 = 23.8$, $K_2 = 44.9$, $K_3 = 10.89$, $K_4 = 0.19$, $K_5 = -10$, $K_6 = 0$, $K_7 = 0$, $K_{clutter} = 1$ are user-defined parameters, h'_{BS} and h'_{UE} are the effective BS and UE heights respectively, by taking into account the earth terrain. L_{diff} is the diffraction loss calculated by Deygout method and $f(clutter)$ is the weighted average of the user-specified clutter losses, in the propagation path between BS and UE. [3]

D. ITU 452 Model

It is based on the ITU-R P.452-15 recommendation [4] and is valid for 100-500,000 MHz band. It takes into account the LoS/NLoS state, diffraction, tropospheric scatter, surface ducting and elevated layer reflection and refraction. It uses the following formula:

$$L_{path} = -5 * log\left(10^{-0.2*L_a} + 10^{-0.2*(L_b+(L_c-L_d)*F_j)}\right) + A_{BS} + A_{UE}, \quad (4)$$

where,

$$F_j = 1 - 0.5 * \left[1 + tanh\left(2.4 * \frac{\theta - 0.3}{0.3}\right)\right].$$

Here L_a is the basic transmission loss due to troposcatter, L_b is the minimum basic transmission loss with LoS propagation and over-sea sub-path diffraction, L_c is the basic transmission loss associated with diffraction and LoS or ducting/layer-reflection enhancements, A_{BS} and A_{UE} are additional losses due to BS and UE surroundings respectively, F_j is the interpolation factor to take into account the path angular distance and θ is the path angular distance. These parameters are further calculated from equations in ITU-R recommendation P.452-15 [4].

E. Performance Comparison

In Fig. 4, a box-plot representation is used to compare the performance of our proposed model with state-of-the-art empirical propagation models, by taking highly precise ray-tracing based RSS estimates as ground truth. The RSS is calculated from the empirical models using $P_{UE} = P_{BS} - L_{path}$, where P_{UE} is the UE's RSS, P_{BS} is the BS's transmit power and L_{path} is the pathloss calculated using (1)-(4). *We can see that the predicted RSS using our proposed ML-based model has much less error as compared to other empirical models, as it's leveraging a novel combination of smart features which are not included in traditional empirical models (e.g. indoor/outdoor distance).*

The performance of our model can even be compared with highly sophisticated ray-tracing based tools, as it's much faster than the latter, a much-complained problem in ray-tracing based tools, by industry professionals. The preliminary implementation of this framework has demonstrated a 12x decrease in prediction time as compared to ray-tracing approach, because it only uses the smart features as input to the trained ML-based model to predict the pathloss, as compared to ray tracing, which approximates the interactions of all rays with the neighboring environment to estimate the pathloss, hence computationally inefficient. Prediction time in our preliminary implementation can be further optimized to make it more efficient (for instance, by using parallel computing).

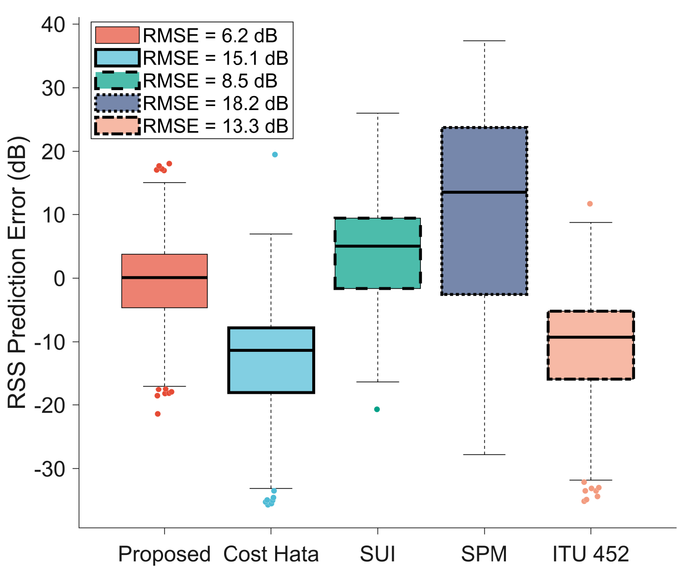


Fig. 4. RSS Prediction Error using different Radio Propagation Models

IV. Conclusion

In this paper, we have proposed a framework for an ML-based 3D propagation model for cellular networks that is scalable and robust to the variation in environment geography. To enable this framework, we have identified a novel set of smart predictors, that can characterize the complex physical and geometric structure of the propagation environment. Performance comparison of several machine learning algorithms is done to highlight their prediction accuracy in modeling the complex wireless channel using the proposed smart predictors as input features. Our results show that overall *Deep Neural Network* algorithm outperforms others even with sparse availability of training data. The preliminary implementation of this framework has shown a 25% increase in prediction accuracy as compared to empirical propagation models, as well as 12x decrease in prediction time as compared to ray-tracing based commercial planning tools.

Acknowledgments

This material is based upon work supported by the National Science Foundation under Grant Numbers 1559483, 1619346 and 1730650. For more details, please visit www.AI4Networks.com.

References

[1] *Urban Transmission Loss Models for Mobile Radio in the 900- and 1,800 MHz Bands: (revision 2)*, ser. COST 231: European Cooperation in the Field of Scientific and Technical Research, 1991.

[2] V. Erceg, K. Hari, M. Smith, D. Baum, K. Sheikh, C. Tappenden, J. Costa, C. Bushue, A. Sarajedini, R. Schwartz *et al.*, "Channel models for fixed wireless applications (IEEE802. 16.3 c-01/29r4)," *Broadband Wireless Working Group, IEEE P802.16*, 2001.

[3] Forsk, *Model Calibration Guide*, AT340_MCG_E0, France, 2018. [Online]. Available: http://www.forsk.com

[4] ITU-R Recommendation P.452-15, "Prediction procedure for the evaluation of interference between stations on the surface of the Earth at frequencies above about 0.1 GHz," ITU, Geneva, 2013.

[5] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, vol. 28, no. 6, pp. 27–33, 2014.

[6] E. Ostlin, H.-J. Zepernick, and H. Suzuki, "Macrocell path-loss prediction using artificial neural networks," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 6, pp. 2735–2747, 2010.

[7] M. Piacentini and F. Rinaldi, "Path loss prediction in urban environment using learning machines and dimensionality reduction techniques," *Computational Management Science*, vol. 8, no. 4, pp. 371–385, 2011.

[8] S. P. Sotiroudis, S. K. Goudos, K. A. Gotsis, K. Siakavara, and J. N. Sahalos, "Application of a composite differential evolution algorithm in optimal neural network design for propagation path-loss prediction in mobile communication systems," *IEEE Antennas and Wireless Propagation Letters*, vol. 12, pp. 364–367, 2013.

[9] M. Ayadi, A. B. Zineb, and S. Tabbane, "A UHF path loss model using learning machine for heterogeneous networks," *IEEE Transactions on Antennas and Propagation*, vol. 65, no. 7, pp. 3675–3683, 2017.

[10] L. Dai, H. Zhang, and Y. Zhuang, "Propagation-model-free Coverage Evaluation via Machine Learning for Future 5G Networks," in *2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. IEEE, 2018, pp. 1–5.

[11] "EGS Technologies," http://www.egstech.com/.

[12] M. Hata, "Empirical formula for propagation loss in land mobile radio services," *IEEE Transactions on Vehicular Technology*, vol. 29, no. 3, pp. 317–325, 1980.

[13] V. Erceg, L. J. Greenstein, S. Y. Tjandra, S. R. Parkoff, A. Gupta, B. Kulic, A. A. Julius, and R. Bianchi, "An empirically based path loss model for wireless channels in suburban environments," *IEEE journal on selected areas in Communications*, vol. 17, no. 7, pp. 1205–1211, 1999.