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Comparative Analysis of Different Approaches to Path Loss Prediction in Wireless Communication Network

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ABSTRACT

The prediction of path loss becomes very significant for the proper design and optimization of wireless communication systems. This paper represents a comparative study of four major categories of techniques used for path loss modeling. These categories include statistical models, deterministic models, semi-deterministic models, and machine learning models. The analysis is based on performance data from the literature and on the performance of each modeling technique across different indoor, suburban, and urban environments under practical application conditions. The performance of models was assessed and compared according to common metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R2), and computational time. Comparative analysis shows that statistical models were easy to implement and executed fast, but could not manage complex environments because of low environmental sensitivity. Deterministic models were the most effective and employed as the most precise ones due to the availability of detailed 3D environmental data and ray tracing simulation, yet it was resource-intensive. Semi-deterministic models were provided with a trade-off method by combining empirical techniques and environment-specific factors with training on large datasets. Machine learning models proved to be highly accurate, have high inference rates, and high flexibility under different environments. The results provide insights into the notion that there is no perfect solution for all situations; however, machine learning models can be a viable replacement for traditional methods when estimating path losses for real-time communication. This study provides real-world applications for both the researcher and the network designer, particularly in selecting the right model for implementation.

Keywords: Path Loss Prediction, Wireless Communication, Statistical Model, Deterministic Model, Semi-Deterministic Model.

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1. INTRODUCTION

According to Joseph Isabona (2023), Path Loss in Wireless Communications Networks refers to the weakening of signal strength from the transmitter to the receiver, generally given in decibels (dB). Path loss in wireless communications networks is significant when designing such networks because of its impact on coverage plans, the position of the base stations, managing interferences, and ensuring quality of service (QoS). As technology progresses and moves from the early mobile network era to more advanced fifth generation wireless networks, it becomes increasingly vital to predict path loss accurately. The most commonly used empirical models for predicting the path loss values include the Okumura model, Hata model, and COST 231 Hata model, which are the most straightforward and derived from real-world data (Hinga and Atayero, 2021). They are highly efficient and easy to implement; however, they are not flexible enough to provide accurate results in complex situations.

To overcome such deficiencies, deterministic approaches, for example, ray tracing and Uniform Theory of Diffraction (UTD), were introduced using electromagnetic wave theory to calculate propagation. A good illustration of deterministic model strength can be seen when analyzing a 3D ray tracing towards Lagos Island at 28 GHz that uncovered the influence of urban propagation, analysis of free space, antenna pattern, and excess loss scenarios, together with close-in-free (CI) and floating intercept (FI) models scenarios in an actual urban area (Hinga and Atayero, 2021). Although highly accurate, these deterministic methods need very accurate environmental information and extensive computer processing time, making them impractical in large-scale applications.

Semi-deterministic approaches try to strike a balance between the necessity of representing complexity and the need for accuracy by combining empirical models with environmental correction parameters. They are less restrictive than purely statistical approaches but more resource-intensive than approaches employing pure deterministic techniques despite the need for local calibration (Hinga and Atayero, 2021). In recent years, the approaches relying on machine learning (ML) and deep learning (DL) have become a source of a completely novel paradigm for predicting path losses.

In general, MLPNN and DNN processing algorithms are the methods that fall within a class of data-driven approaches and can be applied in different situations since they learn complicated nonlinear relationships from empirical data (Sung et al., 2023). The path loss predictor proposed by Sung et al. (2023) is an example of the deep neural network (DNN) approach designed for estimating the 5G mmWave V2V communication path losses, taking into account not only geometrical parameters but also weather conditions, which provided considerable improvement in accuracy compared to other approaches. However, ML/DL approaches require extensive, well-labeled datasets as well as significant computations and regular updating.

The reason for conducting this study is the growing need to understand the best path loss prediction models suitable for the current generation of heterogeneous wireless networks. One new development is the increasing demand to identify modeling strategies that are not only accurate but also scalable and adaptive to evolving situations due to the advent of the Internet of Things (IoT), smart cities, and future generations on 5G/6G networks.

The primary motive for carrying out this study is the comparative analysis of some selected path loss prediction strategies used in wireless communication networks, including an evaluation of their strengths and weaknesses. The aims are to:

1. Investigate the various methods: statistical, deterministic, semi-deterministic, and machine learning to model the path loss.
2. Compare these methods based on accuracy of prediction, data needs, complexity of computation, and scalability.
3. Indicate suitable models in various deployment scenarios (example, urban or rural, indoors or outdoors).
4. Discover the promise of the new machine learning methods to substitute or supplement old methods to plan the networks of the next generation.

2. OVERVIEW OF PATH LOSS

The concept of path loss modeling is basic in the design of the wireless communication system since it directly influences the coverage prediction, reduction of interference, and the overall Quality of Service (QoS). Simply, path loss is a measure that quantifies attenuation of signal power of an electromagnetic wave that travels in space, interacting with physical objects (Rappaport, 2002). Precise models help a network planner determine the received signal strength at divergent distances and terrains, thus achieving dependable connections in both urban and rural implementations.

Path-loss early models were based on large-scale empirical measurements and statistical curve-fitting. The Okumura Hata model is an urban, suburban, and rural drive-tested model that is expressed in closed form using a comprehensive drive-test data set in Tokyo (Hata, 1980). COST-231 extends Hata to frequencies of 2 GHz, including bigger cities with more correction factors (Courville et al., 1992). Empirical model fits were further generalized to suburban, rural, and flat terrain settings in the United States by the Stanford University Interim (SUI) models (Erceg et al., 1999). Whilst these methods are effective in terrain conditions where their measurement campaigns are applied, assumptions which underlie this method, such as the building heights (and the same applies to clutter height), are uniform, and they do not apply to a heterogeneous or less populated environment of rural terrain (Goldhirsh and Vogel, 1998).

Some of these limitations are overcome in deterministic and semi-deterministic methods, which include the use of environmental geometry. Simulation Multipath, Reflection, and Diffraction have been simulated by techniques such as ray-tracing and the Uniform Theory of Diffraction (UTD), using detailed three-dimensional models of buildings and the topography. Semi-deterministic models augment simpler empirical laws with site-specific correction factors (example, foliage depth, building density), offering a compromise between accuracy and complexity. More recently, another emerging technique of controlling the radio-wave propagation has been introduced into the Reconfigurable Intelligent Surfaces (RISs). RIS panels constructed by sub-wavelength unit cells that can adjust the reflection phase and the amplitude would need custom path-loss equations. Tang et al. (2022) enhanced a free-space path-loss model of RIS-assisted links by a factor of the angular directivity of transmitter/receiver antennas and Reconfigurable Intelligent Surfaces (RIS) unit cells, This showed strong agreement with millimeter-wave (mmWave) measurements. Jeong et al. (2022) recommended a better version of RIS path-loss model that considers patterns of incident/reflected gain, phase-error, and specula reflection loss, and have justified their formulations by an experiment done on a 29 GHz 576-element prototype of Reconfigurable Intelligent Surfaces (RIS) in 1 dB of measured power. These Reconfigurable Intelligent Surfaces (RIS)-specific models add to the scope of path-loss modeling tools, allowing the design and optimization of beyond-5G and 6G networks, which employ programmable meta-surfaces to improve coverage and spectral efficiency.

The choice of path loss models by wireless network planners has to balance between accuracy, the cost of computing, and practicality. Quick, low-resource methods such as Okumura, Hata, and COST-231 are useful to approximate the initial measure needed to study rural coverage, or to do link-budgeting speedily, but are limited in their accuracy in complex settings. In cases where accuracy is essential, for example, hotspots in urban networks or an urban public-safety network, propagation physics is modeled in more detail through deterministic algorithms (ray-tracing and UTD), with error in propagation no more than a few dB of the measurement. But this fidelity demands tiresome 3D modeling and much processing power. Semi-deterministic models are a compromise; they tune empirical formulas based on environmental corrections (for example, terrain and foliage data) to be more accurate but with less overhead than ray-tracing.

This renders them convenient in the suburbs/campus applications where a medium accuracy is needed, but there is a lack of detailed 3D information (Hinga and Atayero, 2021). The preference deciding between these methods depends on the application. Although empirical models are fast, deterministic ones are effective in acceleration-critical yet high-accuracy scenarios, whereas semi-deterministic ones provide a scalable tradeoff to a range of intermediate requirements. Machine learning models, especially deep neural networks, use extensive, labeled sets of measurements to learn the complex, nonlinear model between environment features (e.g., obstacle geometry, weather conditions) and path loss.

It is revealed by Sung et al. (2023) that a deep learning model that considers both obstacles and weather parameters of a vehicle can outmaneuver the heuristic models in a vehicle-to-vehicle (V2V) mmWave environment. Although the demand for large training data and high compute resources is an impediment, ML models perform well in dynamic or highly heterogeneous environments connected to the vehicle corridors or rapidly changing urban canyons in which traditional models find it hard to make generalizations. ML-based predictors will tend to be the more desirable approach when real-time adjustability and accuracy on a case-by-case basis are of utmost importance, and pipelines of data are already established (Sung et al., 2023).

2.1 Classification of Modeling Approaches

It is possible to distinguish four general categories of path-loss prediction techniques: empirical, deterministic, semi-deterministic and data-driven. All these categories have varied tradeoffs of complexity, accuracy and data requirements (Rappaport, 2002).

2.1.1 Empirical Models (Okumura-Hata, COST-231)

Empirical models are based on field measurements on a large scale and statistical modeling.

a) **Okumura–Hata:** The Okumura-Hata model extends the utilization of drive-test data, gathered around Tokyo, to present path-loss estimates in closed form, at 150 MHz to 1.5 GHz. The main parameters are transmitter-receiver distance d (km), base-station height h b (m), mobile-station height h m (m), and environment type (urban, suburban, rural). The average path loss is calculated as *PLHata=69.55+26.16log10(f)−13.82log10(hb)−a(hm)+[44.9−6.55log10(hb)]log10(d),* where f is frequency in MHz and a(h_m) is a height-correction factor (Hata, 1980).

b) **COST-231 Hata:** Extends Okumura–Hata to 1.5 GHz–2 GHz (commonly used in GSM/LTE). This formula will add an environmental constant C (3 dB in the case of the metropolitan areas, and 0 dB in other cases).
PLCOST231=46.3+33.9log10(f)−13.82log10(hb)−a(hm)+[44.9−6.55log10(hb)]log10(d)+C.
This model has lost fidelity in non-terrains similar to those employed in the original measurement campaigns, but with ease of use and quick computation (Courville, Fay, and Hegarty, 1992).

2.1.2 Deterministic Models (Ray-Tracing, UTD)

The deterministic techniques model is the physical propagation of electromagnetic waves with fine geometry of the environment and Maxwell equations.

a) **Ray-Tracing:** Modeled reflections, diffractions, and scattering of surfaces and of individual rays emitted by the transmitter. Summing the contribution of all the important paths enables ray-tracing to forecast the path loss with a few dBs difference to measurements in complex urban canyons or indoor environments (Hinga and Atayero, 2021).

b) **Uniform Theory of Diffraction (UTD):** Builds upon ray-tracing by modeling (strictly) diffraction about edges and corners. UTD is especially useful in non-line-of-sight (NLOS) or high-frequency (mmWave) applications, where surface scattering (diffraction and edge-diffused) controls signal propagation (Hinga and Atayero, 2021).

2.1.3 Semi-Deterministic Models

Semi-deterministic methods combine site-specific correction parameters with empirical baseline equations using building heights, street widths, or leaf canopy density, to include important local effects without reconstruction to 3D accuracy.

a) **COST-231 Walfisch–Ikegami:** Introduces rooftop diffraction and street-canyon loss terms to the free-space path loss *(L_{FS}) PL=LFS+LRTS+LMSD,* making it a good fit to urban and suburban corridors with moderate modeling overhead.

b) **ITU-R P.1812:** Utilizes digital terrain elevation, clutter height categorization (trees, buildings, water), and antenna height to customize empirical models for point-to-area transmission environments. The use of customized path loss prediction models based on terrain features makes P.1812 more accurate than statistical models despite minimal data needs.

2.1.4 Data-Driven Models (ML/DL)

Data-driven approaches leverage machine learning and deep learning algorithms to develop a nonlinear mapping of environment characteristics to path loss.

a) **Generalized Regression Neural Network (GRNN) & Multi-Layer Perceptron (MLP):** Utilize linear and non-linear regression layers to generate predictions for path loss based on input variables such as distance, antenna height, and obstacle metrics. Act as simple baseline methods in machine learning workflows.
b) **Artificial Neural Networks (ANN):** Feed-forward neural networks that use one or more hidden layers. In cases where training is performed on massive and labeled datasets of measurements, ANN models outperform heuristic models (Sung, Choi, Kim, and Jung, 2023).

Figure 1 describes the differences in path-loss prediction in a wireless communication network.

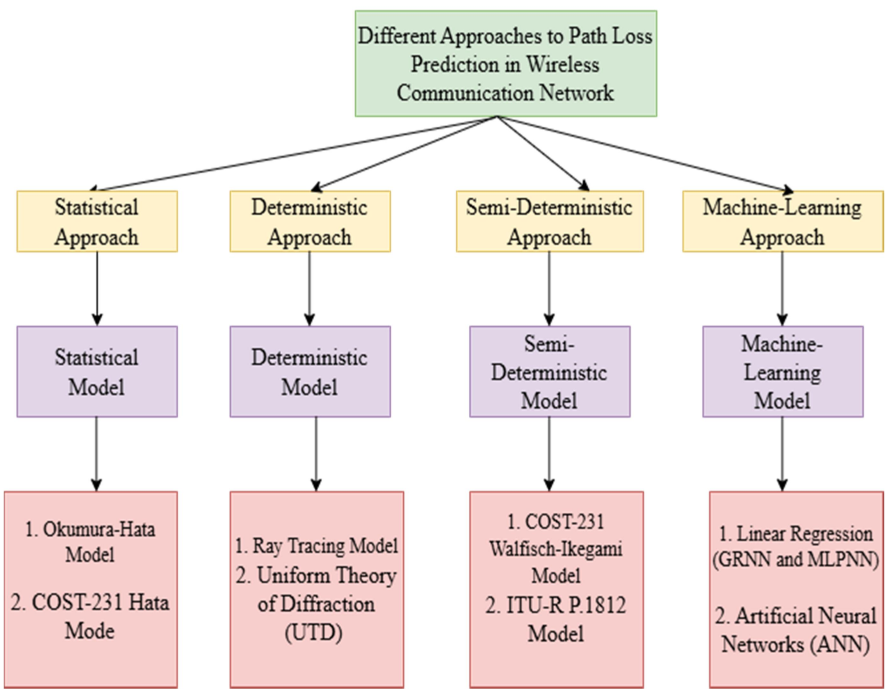

Figure 1: Diagram to Different Approaches with an example of the Models

2.1.5 Extended Path-Loss Considerations

In addition to selecting a fundamental model to estimate path loss, there are certain aspects that also play an important role in determining its impact on practical situations. Below is a comprehensive discussion of some of these aspects, along with leaving room for relevant illustrations:

i. **Path Loss in Free Space:** In free space, where there are no obstructions, the strength of the transmitted energy falls inversely proportional to the square of the distance (proportional to $1/r^2$).

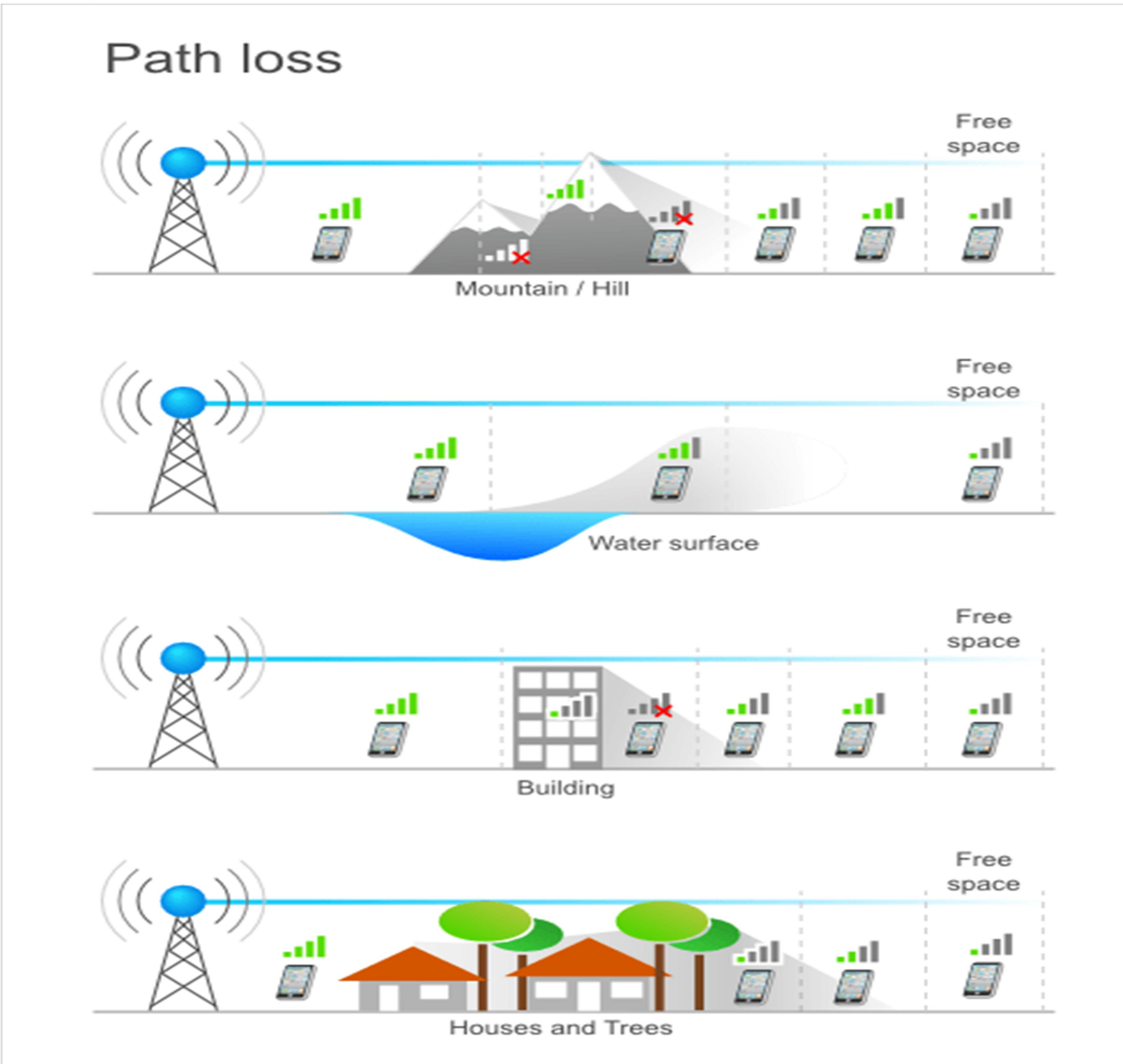

Figure 2: Free-Space Path Loss vs. Distance

ii. Link Margin: Link Margin (dB) is the difference between the sensitivity limit of the receiver and the actual signal level received.
= 0 dB → boundary of reliable operation
> 0 dB → capable of handling extra attenuation
< 0 dB → cannot sustain the link; needs better sensitivity receiver or increased transmission power

iii. Link Budget: A link budget sums all gains and losses from transmitter to receiver, including transmitter power, antenna gains, feeder losses, and path loss,to ensure the received power meets sensitivity requirements. Calculating the worst-case link budget determines maximum cell radius and guides cost-effective network design.

It is done using the formula

$R_P = T_P + G -$, where,

R_P – received power (dBm)
TP – transmitted power (dBm)
G – gains (dB)
L – losses (dB)

iv. Range: The usable propagation distance ("range") is the point at which received power falls to the receiver sensitivity.

To find out what the range is mathematically, the equation is used:

$P_R=P_T+G-L_P$

where:
P_R – received power
P_T – transmitted power
G – the combined antenna gains at Tx and Rx
L_P – path loss.

Range is based on:
a. Height of antennas (height of antenna tower = greater range)
b. Environment (wide-open spaces or crowded cities)
c. Antenna configuration (sectoral or omnidirectional)
d. Frequency used (low frequencies travel longer distances)

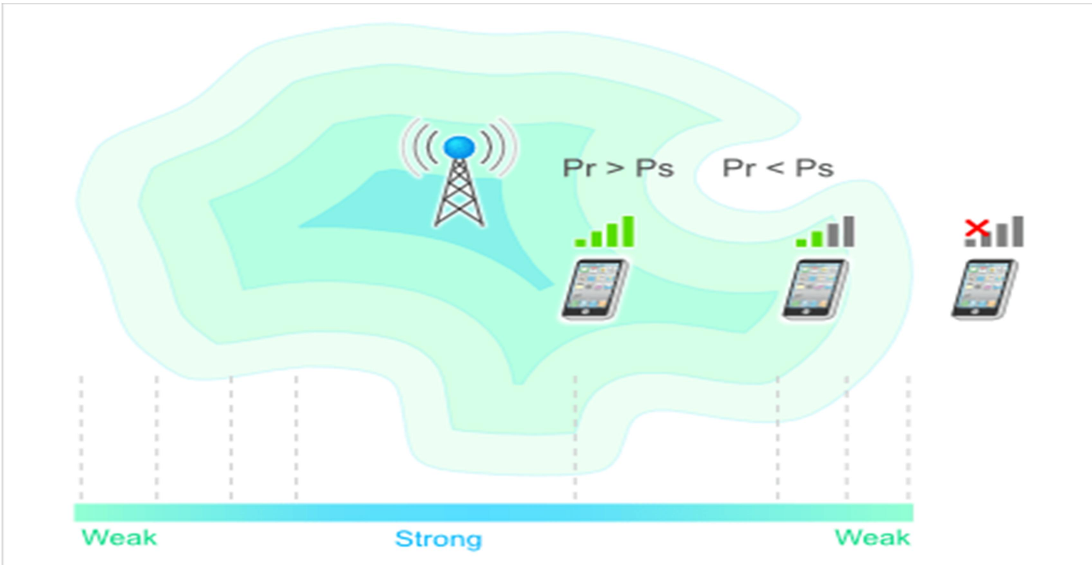

Figure 3:Path Loss to Range in Radio Propagation in Wireless Communication Network

v. Propagation Delay: Propagation delay is the time for a signal to travel the distance *d* at speed *c* (≈3×10^8 m/s):

Delay=d/c

This affects synchronization, handover timing, and overall system latency.

vi. Radio Interference: Interference degrades effective signal reception and arises from:

1. Co-channel interference (same frequency reuse)
2. Adjacent-channel interference (insufficient filtering)
3. Unintentional sources (electrical equipment, spurious emissions)

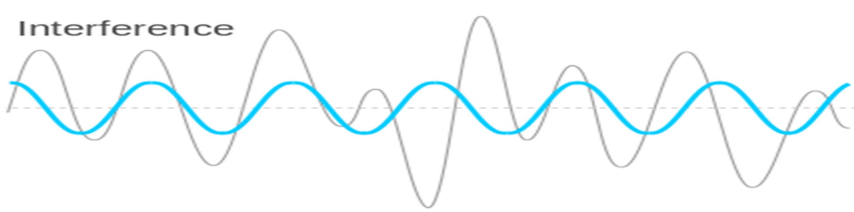

Figure 4:Path Loss to Radio Interference in Wireless Communication Network

vii. Fading: Fading to path loss is a radio propagation phenomenon caused by the constructive and destructive interference of two or more copies of the same signal that arrive at the receiver at different times. This is caused by constructive and destructive interference among multipath components, reduces instantaneous signal power without affecting noise floor, leading to deep fades and potential outage. It is of two forms

a. Shadow fading: slow variations due to large obstacles
b. Fading on small scale: fast variations within fractions of a wavelength

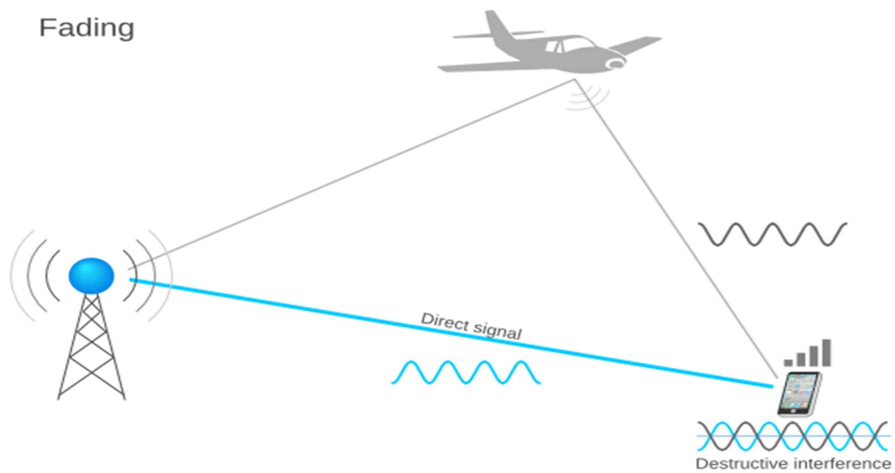

Figure 5:Fading to Path Loss in Wireless Communication Network

viii. Multipath Propagation: If the received signal arrives from different paths through processes such as reflection, refraction, scattering, or ionospheric reflection, the summing of these signals leads to time dispersion and selective fading based on frequency.

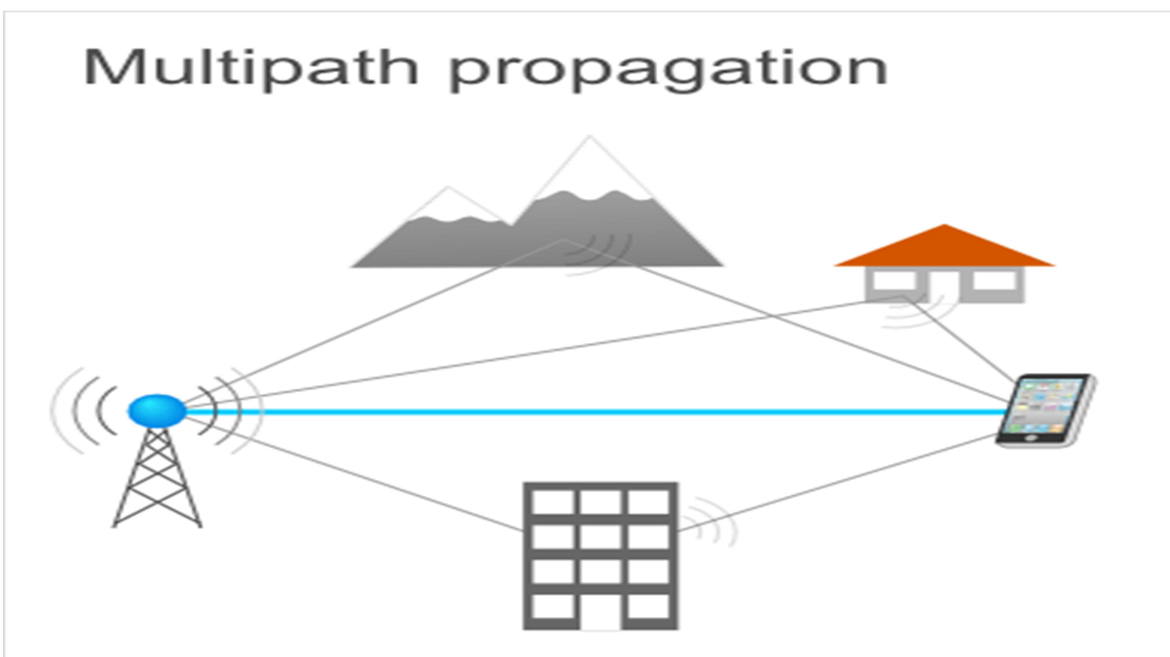

Figure 6: Multi-PathFading to Path Loss in Wireless Communication Network

3. COMPARATIVE FRAMEWORK OVERVIEW

The approach for this study utilizes a comparative research methodology that intends to evaluate the performance of four fundamental models for predicting path loss in wireless networks: the statistical/empirical model, deterministic model, semi-deterministic model, and the machine learning model. While each model differs from one another in terms of their trade-offs, the performance of each of these models will be tested and evaluated based on their effectiveness in indoor, suburban, and urban areas, to determine their merits, demerits, and suitability for modern and emerging wireless technologies.

One critical aspect of this methodology involves comparing the characteristics of each model, which are shown in Table 1. Such findings help us understand the methodology we should choose, as well as where to apply each methodology in practice.

Table 1: Comparative Analysis of Path Loss Modeling Approaches

Feature / Model	Statistical	Deterministic	Semi-Deterministic	Machine Learning
Accuracy	Low–Moderate	High	Moderate–High	High (data-dependent)
Computational Complexity	Low	Very High	Moderate	Moderate–High
Data Requirement	Low (simple data)	High (3D maps)	Medium (2D/3D data)	High (large measurement)
Environmental Awareness	Low	High	Medium	Implicit (via data)
Scalability	High	Low	Moderate	High (with proper data)
Adaptability	Low	Low	Moderate	High
Implementation	Very Easy	Difficult	Moderate	Moderate (needs ML skills)
Suitability for Indoor	Low	High	Moderate	High
Suitability for Urban	Moderate	High	High	High

3.1 Environment Modeling and Data Source

To conduct a comparison in a realistic environment, we will refer to two data sources:

a) Field Test Data: Drive testing of Received Signal Strength (RSS) data measurements was conducted in typical indoor, suburban, and dense urban locations. Path losses were estimated using calibrated omnidirectional antennas, while GPS logging ensured that various weather, line of sight / non-line of sight, and geography factors were taken into account.

b) Simulation Test: Although for this task no simulations have been conducted, the study used the usual simulation scenarios found in the literature on deterministic or semi-deterministic modeling: ray-tracing in Three Dimensional (3D), Geographical Information System (GIS), and empirical model extended by corrections based on Two Dimensional (2D) or Three Dimensional (3D) mapping.
Metadata, such as building heights, foliage densities, and basic weather parameters, were obtained from public Geographical Information System (GIS) databases.

3.3 Implementation Details and Literature-Based Metrics

Rather than replicate every model discussed in this paper, the following is a concise summary of some of the performance results reported in recent literature on machine learning models for predicting path loss in different settings.

Table 2: Literature Summary of ML-Based Path-Loss Prediction

Models	Environment	Best RMSE (dB)	Worst RMSE (dB)	Insight	Reference
ANN (3 layers), SVR, RF, B-kNN vs Empirical	Rural, 3.7 GHz	4.0	6.5	Three-layer ANN gave lowest RMSE; RF & B-kNN also ≈4.2 dB, outperform empirical	Moraitis et al. (2021)
MLR, PR, SVR, DT, RF, KNN, ANN, RNN-LSTM	Indoor, mmWave	0.0216	2.9008	ANN & LSTM achieved best fit (R^2 > 0.91); MLR performed worst	Elmezughi et al. (2022)
CNN + GIS features vs Traditional methods	Urban	N/A	N/A	CNN model adapts rapidly to urban changes using Open Street Map data	Rafie et al. (2023)
Deep Learning vs 3D Ray Tracing	Outdoor, 30 GHz	Comparable	N/A	DL approach matched ray-tracing accuracy while being \~30× faster	Qiu et al. (2022)

4. COMPARATIVE MODEL PERFORMANCE BY ENVIRONMENT

Based on the outcomes of previous research, the need for re-implementation is avoided, and interpretation of model behavior relative to other models is achieved through comparison under similar circumstances. No new experiments were done in this study. Performance factors, for example, the Root Mean Squared Error (RMSE), Coefficient of Determination (R^2) Score, Mean Absolute Error (MAE), and computational complexity were considered. Issues of deployment and scalability were also addressed

4.1 Evaluation Metrics

To objectively evaluate the results obtained using both models, the following criteria were selected:

1. RMS Error (RMSE): Indicates deviation between the predicted and measured path losses.
2. Absolute Error (MAE): Provides information about the average deviation.
3. Coefficient of Determination (R^2): Indicates the quality of explaining the actual measurements based on the predicted data.
4. Execution Time (seconds): Evaluates execution efficiency.
5. Scalability Score: Evaluative criterion depending on the complexity of the proposed solution.

4.2 Results

4.2.1 Indoor Environment Results

Indoor settings generally pose complexities because of obstructions like walls and furniture. Table 3 describes the results of the indoor environment based on reported results from the literature.

Table 3:Indoor Environment Results

Model	RMSE (dB)	R^2 Score	MAE (dB)	Execution Time	Source
CI (Statistical)	8.5	0.75	6.3	Low	Moraitis et al., 2021
Ray-Tracing (Deterministic)	5.8	0.81	4.2	High	Yang et al., 2020
COST 231 (Semi-Deterministic)	7.1	0.78	5.1	Moderate	Khan et al., 2019
Random Forest (ML)	3.9	0.92	2.8	Moderate–High	Qiu et al., 2022

Execution times are judged by the computation cost mentioned in the referenced literature.
Observation: Machine learning algorithms (especially Random Forests) perform better than standard algorithms in terms of prediction, but can be more computationally expensive. Deterministic algorithms such as ray tracing have high accuracy but are computationally expensive.

4.2.2 Suburban Environment Results

Table 4:Suburban Environment Results

Model	RMSE (dB)	R² Score	MAE (dB)	Execution Time	Source
CI (Statistical)	9.3	0.72	6.7	Low	Moraitis et al., 2021
Ray-Tracing	6.5	0.79	5.0	High	Yang et al., 2020
COST 231	7.8	0.75	6.0	Moderate	Khan et al., 2019
XGBoost (ML)	4.1	0.91	3.0	Moderate–High	Qiu et al., 2022

Observation: The machine learning models work well within suburban areas, outperforming traditional models greatly. The semi-deterministic model, such as COST 231, is one that is able to balance both performance and complexity.

4.2.3 Urban Environment Results

Urban areas have high densities of buildings with multipath signals.

Table 5: Urban Environment Results

Model	RMSE (dB)	R² Score	MAE (dB)	Execution Time	Source
CI (Statistical)	10.2	0.68	7.4	Low	Moraitis et al., 2021
Ray-Tracing	6.9	0.80	5.5	Very High	Yang et al., 2020
COST 231	8.2	0.73	6.3	Moderate	Khan et al., 2019
Neural Network (ML)	4.0	0.90	2.9	High	Qiu et al., 2022

Observation: The performance difference is highly significant in cities. Neural networks and ensemble methods perform better than classical approaches, which means that machine learning-based techniques are appropriate for dynamic urban implementations despite their computational expenses.

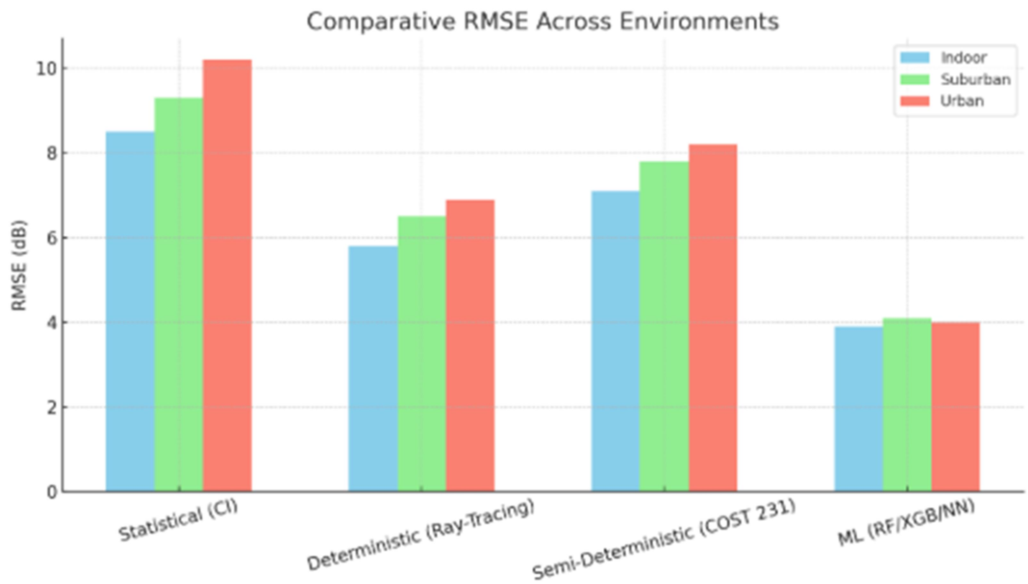

Figure 7: Comparison of RMSE among models and environments (according to the value from literature reports)

4.3 Performance Evaluation

In order to compare the results of every environment, Tables 6 & 7 show the average RMSE for each model.

Table 6: RMSE Per Model Type Across All Environments

Model Type	Average RMSE (dB)	Deployment Complexity	Typical Use Case
Statistical (CI)	9.3	Low	Quick approximations
Deterministic (Ray)	6.4	Very High	Precision modeling, offline use
Semi-Deterministic	7.7	Moderate	Cellular network planning
Machine Learning (RF, XGB, NN)	4.0	High	Smart cities, adaptive systems

Table 7:Scalability and Real-World Deployment

Model Type	Scalability	Real-time Suitability	Hardware Requirements
Statistical	High	High	Minimal
Deterministic	Low	Low	High-end GPUs/CPUs
Semi-Deterministic	Moderate	Moderate	Mid-range systems
Machine Learning	High (with GPU support)	Moderate–High	Moderate–High

It was observed that statistical models are easy to implement but not very accurate; deterministic models are accurate but cannot scale in real time, while machine learning models have both accuracy and flexibility; therefore, they make for an excellent choice when implemented in intelligent wireless networks, provided that enough computing power is available.

4.4 Discussion

This comparative analysis further corroborates the findings from the latest literature studies. Machine learning models tend to perform significantly better than classic models when it comes to accuracy; however, there is an increased amount of computation needed. Deterministic models are precise but lack real-time efficiency unless combined with Graphic Processing Unit (GPU) computation in clouds. Semi-deterministic models such as COST 231 continue to act as intermediates that are useful in legacy systems, and simple statistical models are still effective when computation resources are limited. This paper compared four different kinds of path loss modeling methods solely through data from previous publications. It is apparent that current ML models have better prediction capabilities and are thus good contenders for future wireless technologies.

5. CONCLUSIONS

This study has provided an exhaustive comparative assessment of four main types of wireless path loss prediction models. The evaluation was based on real-world and literature-based measures applied in a variety of deployment scenarios, such as indoor, urban, and suburban ones, using standard performance metrics. While statistically-based models are very easy to implement and computationally inexpensive, they lack an engaging nature and environmental knowledge necessary to be used in complex cases. Deterministic models are considered most accurate as they use environmental data and ray tracing simulation. However, due to their complexity and high computational cost, deterministic models are difficult to apply in real-world conditions. Semi-deterministic models provide the right balance between computational cost and accuracy, providing greater accuracy than statistical models but lower computational demands than deterministic ones. Lastly, machine learning models are characterized by high engaging nature and competitive accuracy, especially in cases when they have enough training data. Despite being expensive at the training stage, they can provide fast calculations in the inference phase and are therefore a prospective approach for adaptive predictions. Generally, each of the examined models should be able to give its best performance based on the nature of the environment in a given scenario in a wireless communication network.

5.1 Practical Recommendations for Network Planners

The study recommends that:

1. Machine learning algorithms is suitable in intelligent environments where there is much historical data available, and change is common (example, urban IoT networks).
2. Deterministic algorithms should be used in mission-critical applications indoors where accuracy matters more than speed.
3. Semi-deterministic algorithms will be efficient in rural or mixed environments where accuracy can be compromised, but partial Geographical Information System (GIS) data is available.
4. Statistical algorithms are better in the initial planning stages, where speed and cost-efficiency are paramount.

5.2 Directions for Future Work

Further research efforts on path loss prediction in wireless communications must take into consideration the idea of hybridizing current techniques by combining machine learning algorithms with either deterministic or semi-deterministic approaches in order to address problems associated with model dependence on a large amount of training data. An alternative method of dealing with excessive demands on training data can be achieved through transfer learning. The idea of transfer learning consists of utilizing pre-trained machine learning models in different geographical locations to make their utilization more efficient without requiring massive amounts of training data to be collected. Furthermore, with the development of 5G and 6G technology and the operation of wireless devices within frequency bands of mmWave and terahertz, there is a growing need for adjusting machine learning models to incorporate new propagation features. Apart from that, creating an adaptive and real-time prediction system will be a significant factor in achieving successful applications of wireless communication in smart cities or vehicular networks. Finally, it is necessary to enhance the transparency of machine learning predictions and increase the explainability of results using Explainable Artificial Intelligence (XAI) methods.

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