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# A Comprehensive Review of Radio Signal Propagation Prediction for Terrestrial Wireless Communication Systems

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**Abstract:** The subject of study known as radio propagation prediction refers to predicting the behaviour and characteristics of radio waves as they propagate through the atmosphere. It is a basic element of all wireless communication systems, including satellite communications, broadcasting and cellular networks. While there is no study covers all the techniques used to predict the radio signal prediction, this study presents a review of the propagation prediction models between 2018-2023 used for terrestrial wireless communication systems; the classic empirical models were briefly explained, followed by the deterministic propagation models that have been developed using ray-tracing with deep and machine learning techniques. Recent studies on an improvement of the computational efficiency and accuracy of propagation prediction models were also reviewed, in addition to an overview of some of the traditional statistical models. Furthermore, some of the new techniques in propagation prediction were described. The results of these studies explain that techniques using ray tracing produce better results than other techniques.

**Keywords:** Machine learning techniques; Neural Network technique; propagation prediction models; Terrestrial wireless communication systems; Computational efficiency.

## 1. Introduction

Mobile wireless communication devices have impacted our daily lives in different ways as they have facilitated human commerce, lifestyle, and social interaction through unrestricted global communication [1],[2]. Companies/operators offer these wireless network services for both non-real-time activities like web browsing to real-time ones like phone and video calls [3]. Performance measures exist for both real-time and non-real-time services. Wireless network operators can maintain and improve network performance while staying within acceptable bounds thanks to these performance measures [4]. By attracting more users and consequently more assets, this respectable performance will keep them from breaking the license regulatory contract.

One of the performance metrics can be the ability to forecast signal propagation in the wireless network with accuracy depending on the design of the network. The primary benefit of prediction is that it is less expensive than field measurements [5]. From one environment to another, the accuracy of propagation models differs significantly and the variance from the propagation model's application context is different from the environment in which it was developed. When these models are used in some nations, the outcomes are disheartening and misleading, leading to an inadequate network design [6]. For instance, several commonly used propagation models, such as Okumura, Hata, etc. when employed in particular cases, such as Japanese cities, can provide extremely good accuracy, but when used in other environments, such as European cities, they will not perform optimally [7]. Other models from the site-specific class, such as Finite-Difference Time-Domain (FDTD), can provide extremely precise findings regardless of the propagation environment, but their applications are restricted by the enormous computation and lengthy prediction times needed for small areas [8].

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Wave propagation is described as the behavior of a wave as it traverses from the transmitter to the receiver in a given medium. Similar to how light waves behave, radio waves are controlled by diffraction, reflection, scattering, absorption, and refraction processes. Knowledge of the effects of each of these events on radio waves has many practical applications, including choosing broadcasting frequencies, building mobile wireless communication systems, radio navigation, and operating radar equipment [9]. A line-of-sight (LOS) connection between the transmitter and receiver may or may not exist in the majority of mobile systems of wireless communication that operate in urban, suburban, rural, and open regions. When there is no clear line of sight and obstructions like mountains, hills, buildings, and trees, there is always a considerable diffraction loss. Due to reflections off the objects in the propagation route, electromagnetic waves move along distinct paths of variable lengths. Multipath fading can occur at specific locations due to the interaction between these waves, and this could lead to decreases in the received wave power as the transmitter-receiver distance increases [10].

Propagation models can be used to estimate and anticipate the RSS based on the transmitter's distance. As a result, propagation models that forecast the mean signal level can be utilized to determine the transmitters' coverage area at a specific location [11]. Given that they estimate the signal intensity across a distance of hundreds or thousands of meters, this type of propagation modeling is on a huge scale. Another class of propagation models is the fading model (or small-scale model), which describes the abrupt changes in signal strength across short distances (on the order of a few wavelengths) or brief periods (of the order of seconds) [12].

The instantaneously detected signal strength may vary when the mobile moves a short distance, causing a quick fading. Energy components that travel through various paths to the receiver from the transmitter contribute to this impact. These energy constituents can mix productively one moment and destructively the next because their phases are random. The received signal intensity can vary substantially (up to 30 or 40 dB) and the phase combination type can change if the mobile travels a very short distance (fraction of wavelengths). The average received signal power will drop as the mobile gets further away from the transmitter (large-scale models). The track of the distances traveled is typically 5 to 40 times the wavelength. This corresponds to a measuring track of 1 m to 10 m for wireless communication networks operating in the 850 MHz to 2 GHz range [12].

The path loss is a model for the power density reduction that occurs when a signal travels from one place to another through a particular medium. The primary element that must be taken into account while designing, analyzing, and optimizing wireless communication networks is path loss. The effects of free space loss, reflection, absorption, diffraction, and refraction lead to path loss. As they control how the parts of the propagating signal fields interact with one another, the propagation environment and operating frequency have a direct influence on the path loss [13]. The signal travels to the receiver from the transmitter in free space, taking the form of a sphere with an expanding radius, which causes the wavefront to widen, causing the free space losses. The signal experiences absorption losses when it enters an opaque material. When the wave is impeded by an object's edge, diffraction losses occur. Refraction and reflection alter the signal route, which indirectly reduces signal strength. A destructive combination may happen at the site of reception if the various components are out of phase.

Prediction is the common name for the path loss calculation; only straightforward situations, like the empty space, allow for exact prediction. In a real-world setting, one of the following techniques [14] is used for path loss estimation:

***I. Empirical approaches (statistical)***: Empirical approaches are based on measurements made in the field of the average signal strength over the distances traveled, such as the Okumura Model, Hata-Okumura Model, and COST 231-Hata Model [14][ 23] [24].

***II. Deterministic methods***: Deterministic methods are based on the physical principles governing wave propagation. The statistical approaches are less precise than the deterministic methods, but the deterministic methods demand more complex computations and a highly precise and thorough description of every object in the propagation space, such as the Ray-Tracing technique [21].

The aim of this paper is to analyze the existing studies of propagation prediction models used for terrestrial wireless communication systems.

The rest of this paper is organized as follows: section 2 expresses an overview of the propagation prediction methods, while section three explains conclusion of this study.

## 2. An overview of the propagation prediction methods

The key pieces discussed in the literature on this topic are outlined in this section

### *2.1 Ray Tracing - based propagation prediction methods*

A 3-D ray tracing (RT) simulation was presented by [15] with a 38 GHz indoor mmW propagation prediction; an additional simulation that was run utilizing the 3-D shooting bouncing ray (SBR) approach was also given. Simulations were performed using the current SBR on a particular layout where the measurement was taken, while the suggested RT approach was also implemented separately. The simulation findings from the RT approach were validated by comparison with the measured data. The output of the proposed RT method, when compared to the SBR approach, showed better alignment with the actual output based on the findings. The mmW propagation can be predicted using the suggested method's ray tracing based on a rough sketch of the real environment, according to the results of the propagation prediction study (see Fig. 1).

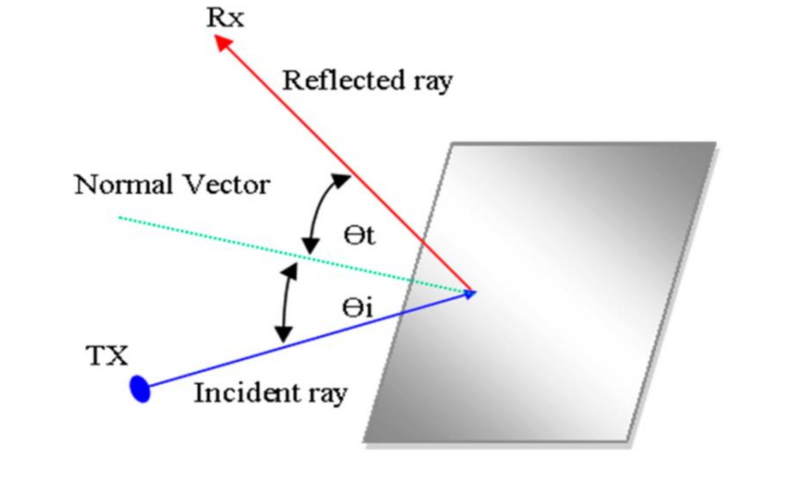


Fig. 1 Geometric representation of the reflection [15].

Table 1 represents antenna configuration details.

Table 1. Antenna configuration details

| SL. | Item | Properties |
|---|---|---|
| I | Gain (dB) | 20 |
| II | Frequency range (GHz) | 26.5–40.0 |
| III | Beam width (deg.) | 18 |
| IV | Waveguide | WR28 |
| V | Material | Cu |
| VI | Output | A Type: FBP 320, C Type: 2.9 or 2.4 mm-F |
| VII | Size (mm) W × H × L | A Type: 40.5 × 32 × 70, C Type: 40.5 × 32 × 95 |
| VIII | | A Type: 0.05 Around, C type 10 Around |

Another study of the 28 GHz indoor radio wave propagation using an effective three-dimensional ray tracing (ETRT) technique has been presented by [16]. The measurement data was used to validate the

ETRT model-based simulation program and the simulation and measurement data showed significant agreement for the path loss and received signal intensity indicator. Hence, the proposed ETRT approach showed significant and better alignment with the actual data than the traditional shooting bouncing ray tracing approach. Acceptable agreement exists for the suggested method based on the comprehensive comparison. The authors concluded that the outcome of the study could guide further studies on 28 GHz mmWave indoor mobile network systems. A general path loss (PL) model is defined as shown in the following equation [16]:

$$p_{Loss}^{CI}\,(f,d)[dB] = P_{Loss}\,(f,d_o) + 10\log_{10}(d/d_o) + X_\sigma \qquad (1)$$

Where: $P_{loss}{}^{CI}(f, d)$ = the PL between the existing TX-Rx spaces at the considered frequency; Ploss(f, $d_o$) = the PL when using close-in (CI) path, $d_o$; $X_\sigma$ = the zero-mean Gaussian random variable (ZMGRV) with standard deviation (SD) σ, in dB. The Measurement setup as in Table 2 **.**

Table 2. Measurement setup [16].

| SL. | Item | Values |
|---|---|---|
| 1 | Carrier Frequency (GHz) | 28 |
| 2 | Transmit Power (dBm) | 25 |
| 3 | Tx Hom Antenna Gain(dBi) | 19.2 |
| 4 | Rx Omni Antenna Gain(dBi) | 3 |
| 5 | Tx Height(m) | 1.5 |

As suggested by [17], a high-resolution environment model can be better captured using point cl oud data (PCD) compared to a conventional geometrical mesh. Hence, PCD is suited for the predict ion of mm Wave radio channels in a new environment. However, the need for repeated propagations using PCD requires more time, and as such, progressive processing was added to improve compatibi lity with other GPU-based models like OptiX & CUDA. With this progressive processing, data with more domain details are generated compared to the surface reconstruction from PCD. For the outdo or environment, the numerical result showed that the new method offers two significant speedups when compared to the when compared to the traditional PCD-based method. The offered speedups by the new method are 18.8 for the total prediction and 49.8 for the ray tracing and field calculation. The prediction was compared with measurement in an urban outdoor environment to portray the efficiency of the suggested method (see Fig. 2).

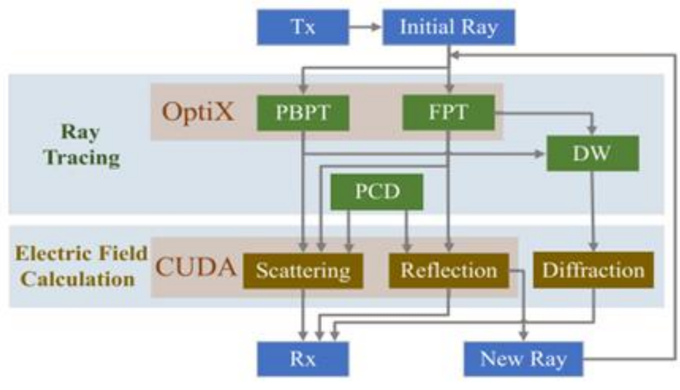


Fig. 2 Flowchart of GPU-based radio wave propagation prediction [17]

### *2.2 Machine Learning - based propagation prediction methods*

The effectiveness of the ELM algorithm for creating a precise model for path loss prediction for outdoor propagation scenarios has been investigated [18]. The Single Hidden Layer FFNNs were trained on path loss data of a commercial 1800 MHz BS along the Lagos-Badagry expressway in Nigeria (see Fig. 3); the data was created using the RSS data, with a focus on both ANN back-propagation and ELM frameworks in terms of their training speed, learning efficacy, and generalization capacity. Then, fresh input data that had not been included in the training procedure was used to test the models and the results showed that the considered ELM and ANN-BP models achieved good prediction accuracy as shown by their $R^2$ values of 0.893 and 0.876, respectively; the models also showed RMSE values of 4.250 and 6.622, respectively. However, the $R^2$ value of the Okumura- Hata and COST-231 models was significantly lower at 0.904 and 0.087, respectively, while their RMSE values were higher at 8.732 and 7.087, respectively. The outcome of the study showed that the ELM method was more effective for the planning and optimization of radio networks in outdoor settings in consideration of its greater prediction accuracy, generalization ability, and quick training convergence.

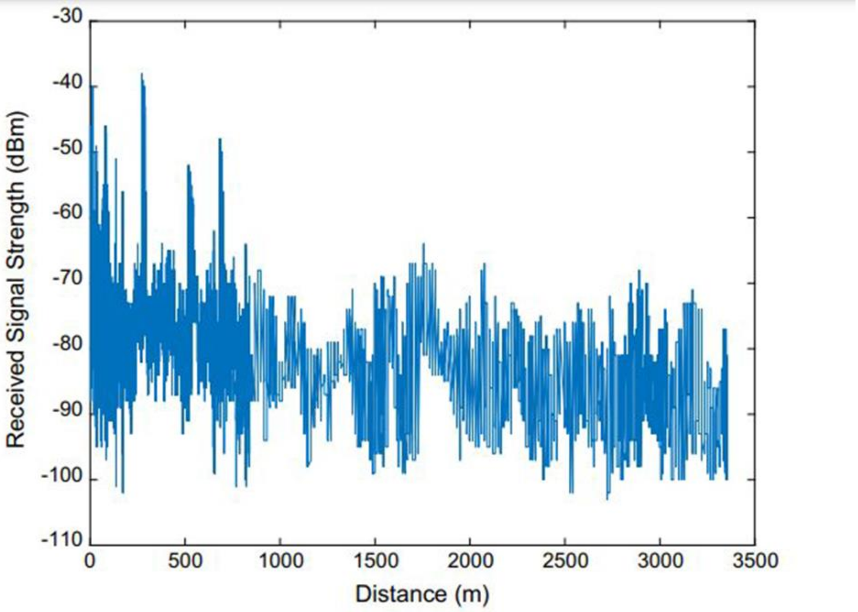


Fig.3. Measurement data collected at 1800 MHz [18]

A machine learning method that attempts latency prediction in an actual network by utilizing real data from a mobile network on the end user has been proposed [19]. The study considered a massive dataset comprising over 238 million latency measurements from three distinct commercial mobile providers. By compressing the RTT values into many bins, the methodology converted the latency prediction problem into a multi-label classification problem. After that, the delay is predicted by utilizing three well-known supervised algorithms. The obtained outcomes showed the importance of the operational network representative dataset and the need for more advancement in the selection, adjustment, and prediction power of algorithms. Data from the MONROE open measurement infrastructure was used in this study to study the delay prediction on commercial mobile carriers. The design of a machine learning program to evaluate the massive amount of data, nearly 238 million RTT measurements of three distinct operating MBB networks, is the novelty of the study.

The theory and methodology of ML-based path loss prediction has been discussed by [20] (see Fig. 4). Various models were evaluated using measured data, including RF, SVR, and ANNs. The study reported that these ML-based models perform better than the log-distance model. However, two methods were provided to increase the training dataset because the number of measured data occasionally falls short of what machine learning algorithms need. On the one hand, historical measurements can be applied to new contexts or frequencies. The classical model can also be used to produce a variety of training samples depending on the historical data gathered from measured outcomes. The efficacy of these data expansion procedures was determined by using the measured data as well.

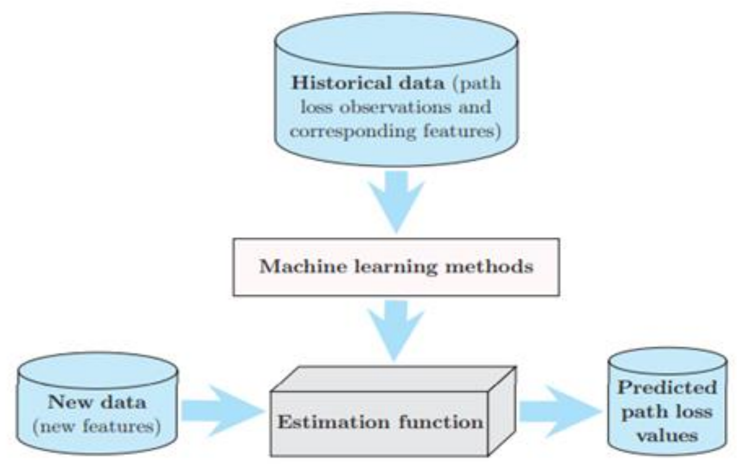


Fig. 4. Principle of machine-learning-based path loss prediction [20].

Machine learning-based models, such as ANN, SVR, and RF, have been shown to perform well with measured data. Two data expansion approaches that fully utilize the available data and traditional models have been put out to meet the demand for training data. The viability of the suggested systems was also confirmed by the measured data. Lastly, the study summarized the issues associated with ML-based models for the prediction of path loss.

A study presented by Nishio *et al* (2019) showed that proactive received power prediction is feasible when using spatiotemporal visual sensing data to build dependable mmWave networks [21]. It is not possible to anticipate the future received power over the long term by analyzing the received signals before the occurrence of a human blockage, which can cause attenuation of the received power on a mmWave link. A revolutionary method has been presented by researchers that can forecast the received power time series several hundred milliseconds ahead of the current moment. The use of image data and ML was the main idea; however, time-series images may have spatial geometry and movement of obstacles that mimic the transmission of mmWave signals (see Fig. 5).

A prediction model is created using ML from a collection of consecutive photos that have been tagged with received power several milliseconds before taking each image. Simulation studies on IEEE 802.11ad devices revealed the ability of the proposed convolutional LSTM-based method to predict the time series of the received power up to 500 ms ahead, with an RMSE of 3.4 dB and an inference time of < 3 ms. Studies with both experimental and simulation datasets showed that the prediction accuracies were significantly high. However, the CNN+ConvLSTM model performed the best out of the three in terms of accuracy.

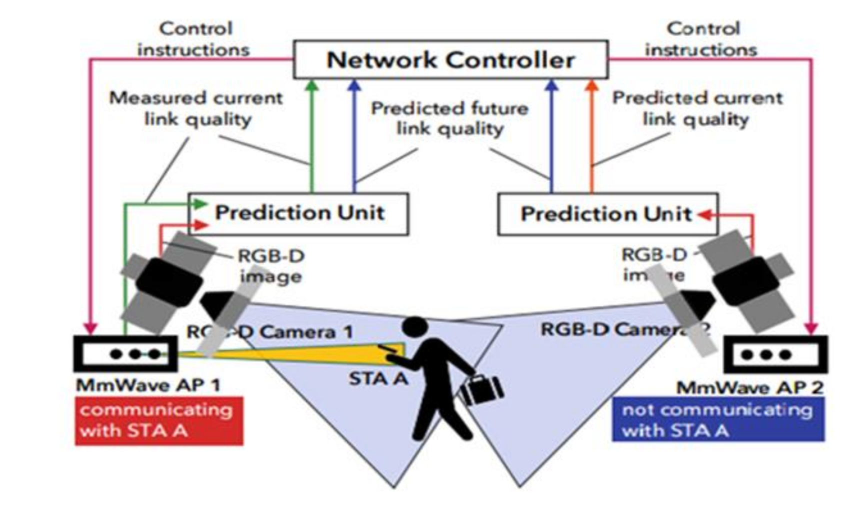


Fig. 5 System model [21].

A comprehensive analysis has been presented [22] to determine the optimal NN parameters for path loss prediction in the VHF band. Significant network and geographic data about the mobile device that was received was also acquired, in addition to field measurements conducted to determine the route losses of radio signals broadcast at 189.25 MHz and 479.25 MHz in an urban propagation setting. Different kinds of NN were trained using varying input parameter types, hidden neuron counts, learning methods, and activation functions for accurate path loss value prediction. Finally, the analysis showed that the proposed ANN-based path loss prediction model performed better generalization and prediction accuracy than the ECC-33, Egli, Hata, and COST 231 models (see Fig. 6).

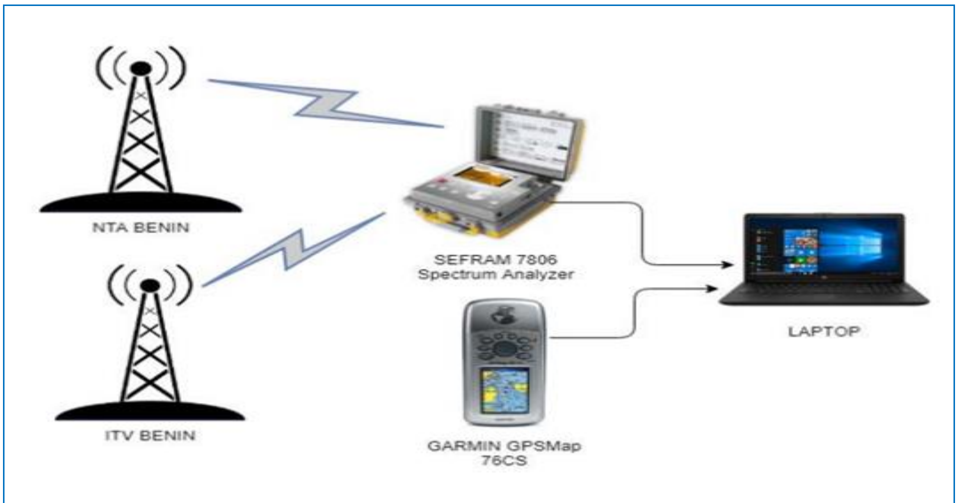


Fig. 6. RSS measurement set-up [22].

A machine learning and building occupancy estimation-based radio propagation prediction approach has been presented [23]. Studies with an emphasis on learning have used building occupancy images and aerial photos as sources of spatial information. However, photographs of building occupancy are often only available in urban settings. The objective is to increase the accuracy of radio propagation prediction by estimating building occupancy photos from the provided images from the air, assuming that only the photos from the air are available. Using U-Net-generated photos increased the received power estimation's RMSE compared to using photographs from the air only. The RMSE between the predicted and measured receiver powers served as the evaluation metric; it was calculated thus:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - \tilde{p}_i)^2} \tag{2}$$

where N = number of data; $p_i$ = value of the actual receiver power; $\tilde{p}_i$ = value of the predicted receiver power.

An ML framework for path loss prediction based on three essential techniques - principal component analysis (PCA)-assisted feature selection, Gaussian process-based variance analysis, and multi-dimensional regression based on artificial neural networks (ANNs) has been presented [24]. The dataset used to measure path loss usually contains a wide range of features such as antenna height and distance. In the beginning, PCA simplifies the learning model by reducing the number of dataset features. The ANN is used to learn the structure of the path loss from the dataset with reduced dimensions while the Gaussian process is used to learn the shadowing effect. The researchers used path loss measurements taken in a Korean suburban area for their study. The accuracy and adaptability of the proposed method were better than those of the traditional linear path loss model.

The use of radio frequency (RF) signals and camera images to improve the prediction accuracy of mmwave received power while collecting image inputs in a way that preserves privacy and communication efficiency has been discussed by [20]. With this goal in mind, the researchers presented a distributed multimodal machine learning (ML) system that divides a big NN into two segments that are wirelessly connected. This approach was dubbed multimodal split learning (MultSL). In contrast to the scenario that is not compressed, the images and received powers are combined in the upper section for the prediction of future received power while the lower half is for gathering camera images' features and compression of the output to reduce privacy leakage and communication costs. The results of the experimental evaluation confirm that MultSL outperformed the baselines in terms of accuracy whether using either RF signals or pictures. Surprisingly, compressing the lower segment output by 16 times results in 2.8 % less privacy loss and 16 times lower communication latency than the case without compression, all without sacrificing accuracy.

The prediction of radio propagation features using an ML-based method called Gradient Boosting has been reported [25]. The model considered building data around the transmitter and a receive site as the features due to their significant impact on radio propagation characteristics. Gradient boosting is a technique for building prediction models utilizing a variety of weak learners, and it allows for the output of the input feature's relevance. In other words, it is possible to measure which feature significantly influenced the prediction of radio propagation and to ascertain the model's efficiency. The prediction accuracy was also evaluated using measured data from an urban region in a bid to understand the impact of the feature difference on the prediction performance. The correlation between the input features and the prediction accuracy demonstrated that by utilizing features that take into account not only the building layout but also other 3D environmental variables such as the height of the building, the prediction accuracy may be enhanced from around 10 dB in the traditional method to around 3.3 dB.

A method for RSS estimation and radio wave propagation modeling based on ML for supplementing the empirical or ray tracing-based models has been proposed [26]. The suggested ML-based model makes use of a pre-identified set of smart predictors, such as transmitter parameters and the geometric and physical properties of the propagation environment to calculate the RSS. There is no need for additional standardization as these intelligent predictors are easily accessible on the network side. The researchers conducted a quantitative comparison of the effectiveness of several ML algorithms in capturing the properties of the channel, even in situations when training data is sparsely available. The results showed that Deep Neural Networks outperform other ML techniques by offering a prediction accuracy gain of 25 % over the state-of-the-art empirical models, and a prediction time decrease of 12x over ray tracing.

Scholars have suggested that drones, AI, and IoT could collectively produce good solutions to some of the issues faced today in smart cities [27]. Drones can travel to places that are dangerous, challenging, or even impassable for people to enter. Drones are just data-gathering machines. These drones have to be in continual communication not only with each other but also with other ground-based agents such as robots, people, and Internet of Things sensors. To anticipate the signal strength from a drone to Internet of Things (IoT) devices in smart cities, this research suggests an intelligent technique. The goals are to determine the drone coverage area, keep the network connected, and provide the required level of quality service (QoS). An efficient and precise artificial neural network (ANN) based approach to signal intensity prediction from a drone has been developed based on different factors, such as route loss, distance, transmitter height, drone altitude, transmission power, receiver height, and signal frequency.

Scholars in [28] employed measured atmospheric factors for the construction of ANN models for RSS computation for 4 VHF broadcast stations. The LMBP technique was considered for the network training. Throughout the training process, various forms of data normalization were used, the number of neurons in the hidden layer was varied, and the impacts of activation functions at the hidden and output layers were thoroughly evaluated. For every network, the mean and variance of the computed MSE over 10 iterations were compared. According to the results, the ANN model did rather well because the calculated values of signal strength fit the measured values well. The MSE calculated by the model ranged from 0.0027 to 0.0043, which is a very low error range. After testing the accuracy of the trained model with various datasets, the obtained results for one dataset in terms of MSE was 0.0069, while for another, it was 0.0040. The measured and predicted field strength showed a good correlation; however, there was no association between the actual field strength and the field strength predicted by the diffraction model. Therefore, using ANN to calculate signal strength based on meteorological data has proven to be a beneficial technique.

The increasing importance of intelligent navigation in automating operations is at the forefront of the Internet of Things' advancement. Logistics, medical, security, and mission-critical indoor scenarios are among the fields where smart navigation and position-tracking technologies are being used more and more. Because of the growing interest in location-based services, indoor localization is a demanding expanding field. In this regard, a variety of indoor localization systems based on inertial assessment units have been proposed. However, there are a lot of issues with these approaches in terms of precision and reliability.

To overcome these problems, a novel location estimation model has been suggested [29] which comprises two modules, one for learning to predict, and the other for estimating position in an interior setting through sensor fusion. The learning module is linked to the prediction algorithm. Furthermore, by analyzing the output and accounting for external elements that can affect the prediction algorithm's result, the learning module continuously monitors, regulates, and improves the prediction algorithm's efficiency. The results showed that the suggested learning-to-predict model greatly increases prediction accuracy, which provides the confidence to investigate its use further to enhance the fun
ctionality of other indoor prediction models.

An ML-based radio propagation model for interior settings has been analyzed previously [30]. The suggested neural network has a dropout layer that is introduced to randomly disable the network units to increase generalization performance. The dropout layer receives the ambient feature input parameters, which include materials, ceiling height, and floor size. For test data, the suggested model's RMSE is less than 5 dB, and its average accuracy surpasses that of the traditional model.

Intelligent techniques for connecting the IoT with unmanned aerial vehicles (UAVs) with optimal network connectivity and required quality of service (QoS) have been suggested [31]. Adaptive data transmission is made possible by the prediction of signal strength and fading channel conditions, which improves end users' and devices' quality of experience while using less power for data transmissions. UAVs are robots that collect data from areas that are hard or impossible for people to access. Thus, the atmosphere and atmospheric dynamics affect the signal strength while humanity, IoT devices, and UAVs are flying across space. As a result, the smart UAV's signal is subject to attenuation, reflection, diffraction, scattering, and shadowing factors. They examine ANN's capacity to use physical media properties and drone data to predictably estimate signal intensity and channel propagation. In addition, the outcomes prove that the signal's distortion can be much improved and decreased.

### 2.3 Deep learning- based propagation prediction methods

Deep Channel, a sequence-to-sequence DL model based on an encoder-decoder that can predict future variations in wireless signal strength based on historical signal strength data has been developed by [32]. The researchers studied two distinct iterations of Deep Channel, where in the initial version, LSTM was used as its fundamental cell structure, while the subsequent version uses GRU. Specifically, they take into account Zigbee networks functioning under different user mobility levels, 4G LTE, Wi-Fi, Wi-MAX, and an industrial network running in the 5.8 GHz range, and these networks all show that Deep Channel performs noticeably better. Lastly, the researchers offered a thorough analysis of the main design choices, along with insights into optimizing hyper-parameters and the model's suitability for use in different networking contexts. The experimental results showed Deep Channel's robustness and wide applicability. The MAE, RE, and RMSE values were calculated for the model to determine its performance. While RE captures the portion of the prediction error related to actual channel variation, RMSE and MAE capture the error in the absolute prediction.

A new analytical model that incorporates latency, radio resource waste, call dropping, and signaling overhead for the holistic handover (HO) cost evaluation presented has been [33]. The created mathematical model can be applied to various cellular structures. Furthermore, a proposal for data-driven HO prediction was made as a holistic cost component through the creative use of a stacked long-short-term memory (LSTM) model, a recurrent deep learning architecture. Lastly, depending on HO management requirements, simulation findings, and early analysis show many scenarios where DNNs (predictive and non-predictive) can be used successfully. The researchers concluded that reduced latency, signal overhead, resource waste, and user discontent can result from the created model combined with a data-driven, deep-learning method. Thus, the cutting-edge model is proposed as a reference point for the machine learning and mobile networking sectors (see Fig. 7).

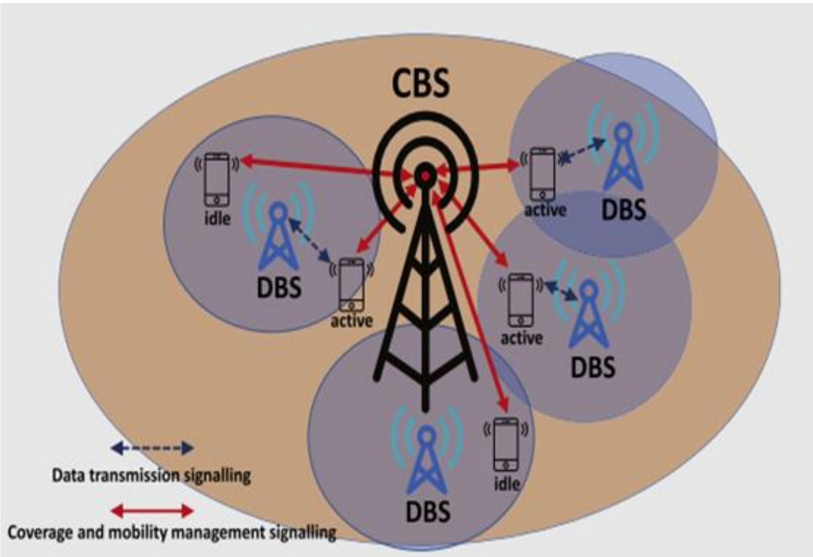


Fig.7 Sample CDSA architecture [33].

The study by [34] first showed that the ideal mmWave beam and blockage status can be efficiently predicted from the sub-6 GHz channel using mapping functions as long as certain provisions are made. However considering that these mapping functions are difficult to describe analytically, DNN models are being used to train them. To do this, they proved that mmWave beams and blockages may be predicted by a neural network of sufficient size, with success probabilities that can be brought arbitrarily close to one. The tests on beam prediction show an intriguing tendency of the network to figure out the right beam direction. Even if it occasionally gets the mmWave beam wrong, it frequently chooses a beam that is close to the ideal one. At suitable SNRs, this can be achieved with both small and large mmWave antenna arrays. This performance also applies to the blockage prediction task, where the network can forecast the LOS connection status with over 90 % success probability at high SNRs; this may bring about significant improvements in mmWave system reliability.

Researchers have demonstrated the use of a DNN for predicting radio propagation [35]. The DNN can work with non-linear functions, so, there is no need to derive complex functions. This means that for radio propagation prediction, the DNN can learn the necessary environmental parameters from input spatial information such as map data. Additionally, the DNN can learn the characteristics required for using input data. The researchers examined the relationship between the variety and quantity of input data from numerous perspectives and evaluated the DNN-based propagation prediction performance with the actual data in an urban setting. The evaluations showed that using the occupancy rate of a building is more efficient than using aerial photos as input data. Moreover, it was evident that combining Tx and Rx image data resulted in an estimate with similar accuracy levels as using other input data. The most effective technique to reduce computational complexity is to reduce the amount of picture data; nevertheless, it is also proposed that reducing the number of weight parameters is appropriate to preserve estimation accuracy.

The researchers in [36] found dramatically increased performance when compared to conventional models following the use of a novel approach for radio propagation modeling using DNNs. The basis for data-driven radio propagation modeling was also laid, allowing for the use of rich and unconventional site information, such as satellite pictures, in future studies to produce more precise and adaptable models. The researchers showed that the suggested solution is significantly more accurate and computes much faster with modern GPUs using real field data.

A novel DL-based path loss prediction model that relies on the top-view image of the receiver position for implicit extraction of radio propagation properties has been presented [37]. The proposed method was applied to a real-world large dataset comprising 5 distinct situations and over 125,000 unique entries in a thorough evaluation campaign. They described a hybrid strategy for path loss prediction and radio environmental map construction that combines model-based and data-driven methodologies. Top-view photos of the receiver environment (which has performed exceptionally in image classification) were also used on the deep learning model to develop geographical radio environmental prototypes.

In the study by [38], a channel model developed by DL approaches using satellite images with the assistance of a basic path loss model was benchmarked against traditional channel models. The training and testing datasets comprised the collected experimental measurements. This research compared and evaluated path loss modeling methods provided by modern stochastic models with a ray-tracing model. The results indicate that the model-aided technique provides an improvement of approximately 1 dB in predictive performance; the satellite images offered an increase of about 0.8 dB in predictive performance. Finally, the proposed DL model can improve path loss prediction by ≈ 1 dB & ≈ 4.7 dB for 2630 MHz at unseen locations (see Fig. 8).

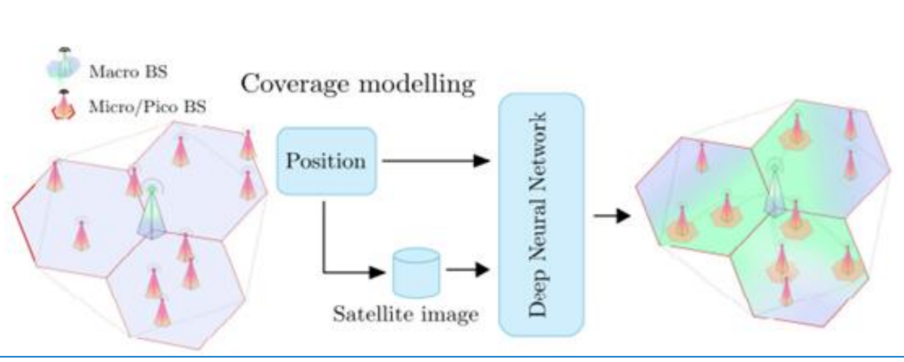


Fig. 8 Complex channel models are needed for coverage prediction in complex scenarios [38].

The accurate prediction of PL requires accurate prediction of the transmitter coverage and optimization of the performance of a wireless network. It is challenging for traditional PL models to keep up with the growing trend of various, time-varying, and huge wireless channels. To accurately predict PL, the most popular MLP neural network in ANN is used in the work reported by [39]. Rather than utilizing complex 3D environment modeling, three categories of environmental features are identified and retrieved, which just represent the propagation environment by taking into account a small number of environmental types. PCA is used to create low-dimensional qualities of the environment and remove redundant data among comparable environmental types; the measurements also provide information about the receiver (Rx) and the base station (BS), such as 3D locations, frequency, antenna data, feeder loss, the transmitted power of the BS, and the received power of every site. The information of BS and Rx is coupled with various environmental factors to create seven datasets for MLP neural network-based PL prediction models. The study strived to understand radio wave propagation properties, which can serve as a theoretical basis for communication system design and wireless network optimization (see Fig. 9).

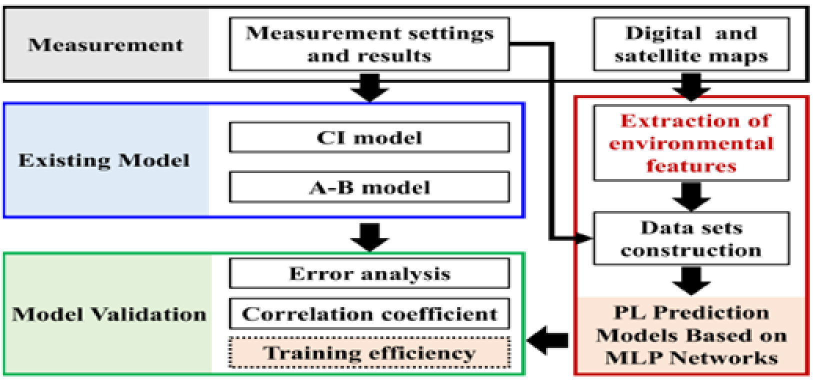


Fig.9 The workflow of PL prediction models [39].

Spectrum data learning and solving difficult tasks in 5G and beyond, such as beam selection for initial access (IA) in mmWave broadcast using DL-based algorithms have been presented [40]. Using RSSs from a subset of possible narrow beams, a DNN may forecast, for directional broadcasts, the beam that is ideally slanted to each user equipment (UE). The researchers suggested an adversarial attempt to trick the IA's beam selection procedure, which is based on a DNN classifier that predicts the beam that is most effectively orientated toward the receiver using only a subset of available beams. The study looked at two different attacks which are the non-targeted FGM and the k-worst beam attacks. The aim of the former is to deceive the DNN classifier by misclassifying any other beam label, while the latter only tries to trick the DNN classifier by tricking it into believing that the label chosen at the DNN is in one of the k-worst beams. They demonstrated how an adversarial approach can drastically reduce the DNN's accuracy and trick it into choosing the poorest beam.

Radio signal strength field prediction in an urban setting using deep neural networks (DNNs) has been reported [41]; the work relies on a 3D map of the surrounding area and signal strength samples gathered throughout the prediction space to forecast the radio waves' scattering through the environment. The massive data availability allowed the effective simulation of complex physics problems using large-scale ML and ANNs. Inspired by ANN's success in physics modeling, the researchers used DNNs for radio signal strength field prediction in an urban setting. To predict how radio waves would scatter throughout the environment, the system makes use of 3D maps of the surroundings and samples of signal intensity gathered throughout the prediction space. The researchers determined the operating variables, explained the assumptions, and specified the conditions in which the algorithm is intended to function. In this study, they describe a DL method that can effectively achieve this goal and show how deep learning may be used for radio signal propagation prediction in an urban area. The performance of the algorithm was better than that of the benchmark in terms of predicting signal strength as the algorithm achieved a stochastic signal strength prediction due to its effective use of 3-D maps.

Propagation models are mostly used to choose radio transmitter locations; this is aimed at ensuring maximum coverage in the region of interest. However, it is often expensive to find accurate power measurements across a region for a given set of transmitter locations and this has necessitated the need for quick prediction methods that can predict the power values given the available data. Researchers took into consideration a dataset that includes simulated power for a specific set of transmitter locations at every position in an area. For instance, various ML models, such as NNs, KNNs, and Generalized Linear Models (GLMs) have been used to predict the power values for specific transmitter sites [42]. To improve the ML models' prediction performance, the study looked into several feature engineering techniques and found that the prediction accuracy is much increased when using feature selection methods to cluster distances. The analysis showed better performance of simpler models such as GLM and KNN as they required less computational power than the complex MLP and DNN (see Fig. 10).

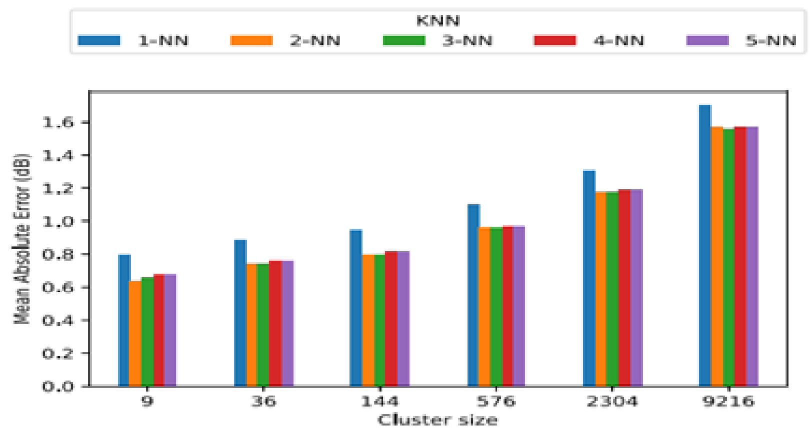


Fig. 10 hyper parameter search results [42]

A deep learning approach for calculating the propagation path loss on a planar domain from a transmitter site, point x, to any other point y, with high efficiency and high accuracy has been proposed [43]. They demonstrated that deep neural networks when appropriately trained and configured, can learn to estimate the path loss function in an urban setting with high computational efficiency and accuracy. With the use of a physical simulation dataset, the suggested technique, called Radio UNet, learns to produce path loss estimates that are extremely similar to the simulations but significantly faster to compute for real-time applications. Additionally, they offer methods for applying simulation-based learning to real-world situations; this strategy performs noticeably better than other ways that have been suggested, according to numerical results. Accurately understanding the path loss function for every pair of transmitter-receiver sites is crucial for applications like user-cell site association and device-to-device link scheduling. Statistical models that are frequently employed approximate the path loss as a decreasing function of the transmitter and receiver's distance. However, such radial-symmetric functions produce very deceptive results in genuine propagation contexts that include items at varying heights, street canyons, and buildings.

A costly step in determining the ideal transmitter placement with ray tracing software is accurate radio frequency power prediction in a given geographic area. The researchers in [44] empirically analyzed the viability of DL models to speed up this procedure. In particular, power prediction tasks can benefit from the application of DL techniques like CNNs and UNET, which are commonly utilized for segmentation. They considered a dataset comprising radio frequency power levels for four distinct frame dimensions and five distinct areas. They compared DL-based prediction models, including RadioUNET and four other variants of the UNET model for the power prediction challenge. The model performs better on higher quality frames, like 256×256, when using more complicated variants of UNET. The detailed numerical study showed the DL models can effectively predict power and display good generalization to new regions.

A unique MLP-NN-based model for path loss prediction has been reported [45], together with a guided implementation network architecture and a method for hyperparameter tuning based on grid searches. The suggested model is built to approximate route loss between the BS and the mobile station as best as possible. The number of neurons, learning rate, and hidden layers are some of the hyperparameters that were considered. For comprehensive route loss experimental datasets, the constructed MLP model's prediction accuracy level has been used, employing a variety of learning and training techniques with tuned best values for the hyperparameters. The collection of the experimental path loss data in the urban microcontroller setting was done using the field drive test for an operational 4G LTE network. Several first-order statistical performance measures were used to evaluate the proposed model for accuracy which showed up to 50 % improvement on the acquired LTE path loss datasets compared to the standard models.

### *2.4 Propagation of ad hoc wireless local area - based propagation prediction methods*

The propagation of ad hoc WLANs operating at 2.4 GHz and 5 GHz, which are commonly employed for near-shore autonomous surface vehicle operations, was studied by [46]. The same physical equipment was used in nearly the same location to collect RSSI data at two different frequencies over land and seawater, as well as two different ground station antenna heights to isolate the marine environment effect. The findings indicate that when moving from over-land to over-seawater, the proposed 2.4 GHz, 2 m antenna height system experienced a 2 to 3 dBm path loss (corresponding to a 25 to 40% reduction in range). The findings indicate that during the over-land trials, $R$ stayed generally constant at $-0.49 \leq R \leq -0.45$. On the other hand, during the over-seawater studies, R showed a frequency dependence, varying between $-0.51 \leq R \leq -0.50$ at 5 GHz and $-0.39 \leq R \leq -0.33$ at 2.4 GHz. Previous studies have evaluated the performance of maritime radio frequency (RF) propagation by obtaining RSSI data over water and contrasting it with present propagation models. However, the problem is that these single-domain studies have not cleared the difference between maritime environment-specific elements and those specific to the normal terrestrial RF systems. The following equation was used for the conversion from the mW to dBm scales [46]:

$$P[\mathrm{dBm}] = 10 \cdot \log_{10}\left(\frac{P[\mathrm{mW}]}{1[\mathrm{mW}]}\right)$$
$$P[\mathrm{mW}] = 10^{\frac{(P[\mathrm{dBm}])}{10}} \tag{3}$$

The Friss transmission formula, given in Equation(8), is the basis for the free-space path loss (FSPL) model [46]:

$$\frac{P_r}{P_t} = \frac{G_t G_r \lambda^2}{P_l (4\pi d)^2} \tag{4}$$

### *2.5 The Okumura-Hata model, the COST 231 Walfish-Ikegami (COST-WI), and the COST-231 Hata model*

The simulation of radio propagation for LoRaWAN at 868 MHz in an urban setting has been performed using 3 models - the Okumura-Hata, the COST-WI, and the COST-231 Hata models in the NS3 [47]. LoRaWAN employs 868 MHz as its radio frequency. The validity and reliability of the empirical models are evaluated by comparing the expected RSS values with real measurements taken in Glasgow when used for LoRaWAN network planning and prediction. In the Glasgow city scenario, Okumura-Hata underestimated the RSS while COST-WI overestimated the same power, according to the comparison of the models and measurements. In a similar vein, the best and worst prediction accuracies were recorded by the Okumura-Hata and COST-WI models, respectively. To predict the received signal intensity in Glasgow, UK, empirical propagation models were used to simulate LoRaWAN operating at 868 MHz in NS3l; the employed models are COST-WII, Okumura-Hata, & COST-231 Hata (see Fig. 11).

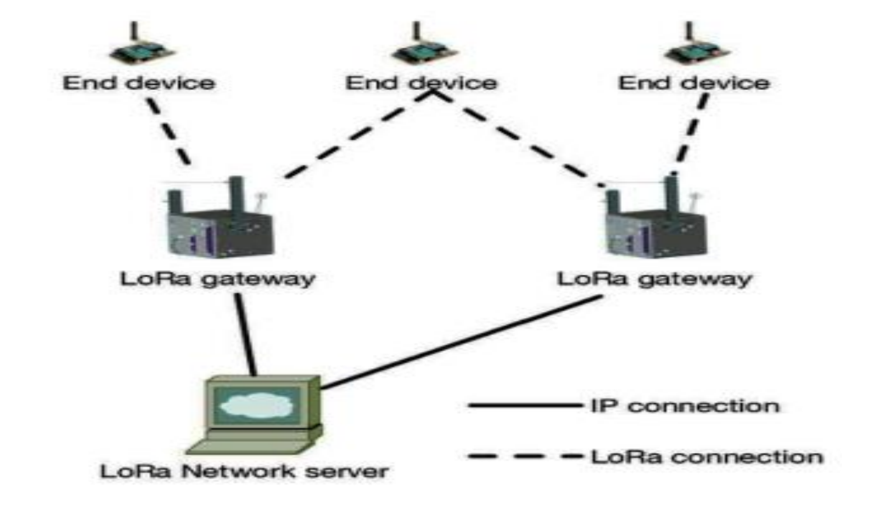

Fig.11. LoRaWAN Network Architecture [47].

For the urban areas, the path loss equation for the Hata model was given as follows (in dB) [47]:

$$P_{Loss} = 69.55 + 26.16\log_{10}(f) - 13.82\,log_{10}(h_t) - a(h_r) + (44.9 - 6.55\,log_{10}(h_t)\,log_{10}(d)) \quad (5)$$

Where the correction factor a($h_r$) is given as follows [47]:

$$a(h_r) = (1.1\ \log_{10}(f) - 0.7)h_r - (1.56\log_{10}(f) - 0.8)dB \quad (6)$$

The path loss prediction of the COST 231-Hata-Model is based on the fundamental system characteristics, which vary from 1–20 km for distance, 1500–2000 MHz for frequency, and 1–10 m for end-device height and 30-200 m for gateway antenna height. The mathematical relations for the many applications of this paradigm are given below [47]:

$$P_{Loss} = 46.3 + 33.9\log_{10}(f) - 13.82\,log_{10}(h_b) - a(h_m) + (44.9 - 6.55\,log_{10}(h_b)\,log_{10}(d)) + c_m \quad (7)$$

The variable $ah_m$ for urban areas is given as [47]:

$$a(h_m) = 3.20\,(log_{10}(11.75h_r))^2 - 4.97, for\ f > 400MHz \quad (8)$$

and as below for rural or sub-urban areas [47]:

$$a(h_r) = (1.1\ \log_{10}(f) - 0.7)h_r - (1.56\log_{10}(f) - 0.8) \quad (9)$$

### *2.6 Wavelet - based propagation prediction methods*

A novel approach for predicting spatial electric field strength, called Wavelet-GRNN has been proposed [48]; the approach combines wavelet-based decomposition with a GRNN neural network model, which captures important information for robust predictive learning. The processing of the spatial field strength data was done using a three-level wavelet decomposition approach and the deconstructed elements serve as input data for the GRNN model. In the third phase, the wavelet coefficients are combined with the GRNN predictor's outputs to form the final projected output of the model. To evaluate the prediction accuracy of the Wavelet-GRNN model, six different first-order statistics are used and compared with alternative prediction strategies. The proposed Wavelet-GRNN model performed better in predicting the values, with mean absolute error ranging from 0.18 to 0.37 in all six study locations. On the other hand, the standard MF-GRNN and GRRN predictions demonstrated a much wider range of mean absolute error values, ranging from 2.44 to 4.69 and 0.42 to 0.96, respectively (see Fig. 12).

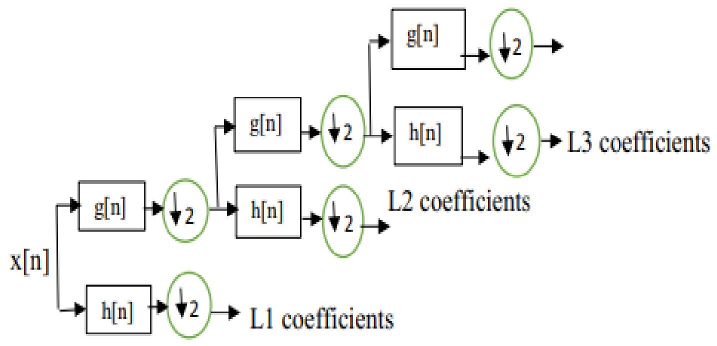


Fig. 12 Three decomposition level to be used as input to the GRNN [48].

### *2.7 Random forests (RFs) - based propagation prediction methods*

To enhance signal strength maps acquired from sparse measurements, a prediction framework based on random forests was presented by [49]. First, a predictor was proposed based on RFs with several features, ranging from device hardware, time, and location, to cell ID. The analysis showed that the proposed RFs-based model improved the balance between the number of needed measurements and the prediction error as it required 80% fewer measurements to achieve the same level of prediction accuracy; this implies about 17 % reduction in relative error for the same number of measurements. Second, the performance of the various prediction techniques was assessed on two different real-world LTE RSRP datasets: (i) a sparser but still compact Campus dataset collected from a university environment; and (ii) stronger NYC & LA datasets provided by a company that analyzes mobile data. The study used RFs, a potent technique that has been modified for this situation, by assessing many attributes. The datasets under investigation offer unique insights into the prediction of signal maps for an entire city and are the largest used in this regard.

### *2.8 Adaptive Neuro-Fuzzy Inference System (ANFIS) - based propagation prediction methods*

The development of a path-loss model for accurate estimation of the wireless High-Speed Packet Access (HSPA) network signal in Ibadan, Nigeria, has been reported [50]; the model was developed using the ANFIS. The RSS from 3 BTS working at the frequency of 2100 MHz was measured using the Drive Test in the Ibadan areas of Ojo, Dugbe, and Challenge. RSS data gathering at different distances was achieved using different systems, such as GPS, Ericson Test Equipment for Mobile System (TEMS) phone, and computer systems. The developed ANFIS model was trained and tested using different input variables, such as the carrier frequency, BS distance, and the transmitter and receiver antenna. The suitability of the Okumura-Hata, COST-231 was also tested using these BS parameters (see Figure 13).

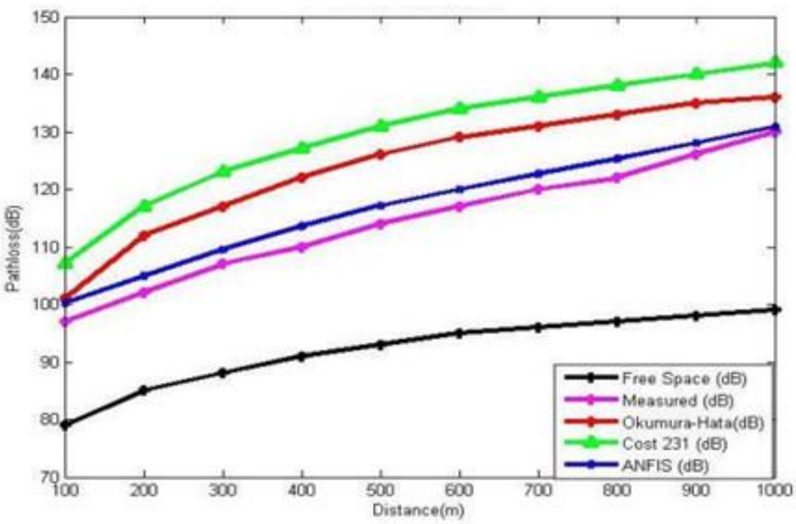


Fig.13 Path-loss versus distance for ANFIS, Measured, COST 231, Okumura-Hata and Free space models for $BTS1$ (Ojo) [50].

### 2.9 The finite-difference time-domain (FDTD) and alternating direction-implicit parabolic equation (ADI-PE) techniques - based propagation prediction methods

Huang et al. [51] presented a cost-effective hybrid method that combines the FDTD and ADI-PE techniques for accurate and quick deterministic 3D radio wave propagation forecasts with intricate structures in both far and near-field scenarios, especially in challenging terrains. The study employed a Woodbury-formula-based parallel algorithm to calculate inverse matrices of tridiagonal matrices in a bid to address the inefficiencies of the parallel ADI-PE models. This is to permit the completion of the explicit and implicit steps of the PE on local computing cores, resulting in improved simulation efficiency in bandwidth-constrained environments. The simulation results showed the ability of the proposed approach to achieve cutting-edge performance. The method is more flexible and helpful for real-world scenarios with irregular geometries, and it also has a lower computing cost compared to other approaches based on experimental data.

### 2.10 ITU Model

For 5G systems and beyond, the precision of rain attenuation prediction is essential for predicting signal strength and link budget for short-range mm-wave terrestrial links. The study by [52] focused on improving the rain attenuation forecast over mmwave frequencies for a short-distance channel (< 1 km). Interestingly, the ITU-R P.530-17 rain-induced attenuation prediction at 26 GHz and 38 GHz in Malaysia, with a path length of 300 m, obviously overestimated the actual data due to the considered distance which ranged from 2.5 (f = 38 GHz) to 2.54 (26 GHz). After a thorough investigation, it was discovered that the distance factor's maximum values were inconsistent for paths less than one. To minimize the predicted-actual value variation, the parameters of $I_{f\gamma}$ are adjusted using the rain attenuations recorded at 26 and 38 GHz.

Singh et al. [53] conducted a thorough analysis of computational intelligence-based techniques for forecasting and assessing attenuation caused by external causes when designing radio links. Additionally, a modified ML-based intelligent prediction model was used for predicting rain-induced attenuation. But this model only needs the rain rate in mm/h and frequency in GHz and as such, is less complex than the ITU model; it also does not require the values of the regression coefficients k and α, in contrast to the ITU model. This model is useful for predicting the attenuation caused by rain at different rates at specific higher frequencies. This feature is helpful for researchers and engineers. With only two inputs, frequency in GHz and rain rate in mm/h, this model can predict attenuation due to precipitation.

## 3. Conclusion

As wireless communication expands quickly, new methods and concepts are required to boost capacity and enhance quality of service (QoS). More complicated ecosystems and smaller cell sizes must be effectively modeled to reach these higher frequencies. For the best design of next-generation communication systems, this necessitates the creation of propagation prediction models tailored to individual sites. The ray-tracing approach is one such model that can give statistics parameters, path loss, arrival time, angle, and other information for propagations in complicated environments. On the other hand, characterizing the walls of intricate structures and creating ray-tracing models that are comparable to windows and metal-framed buildings present new difficulties. Solving these problems requires new advancements in computationally effective ray-tracing techniques that can open the door for the construction of an integrated indoor/outdoor urban propagation model that addresses the intricate indoor/outdoor interface problems. The results of these studies explain that techniques using ray tracing produce better results than other techniques. The previous researches produced results, but they were not very accurate. Therefore, the new direction of researches involves using ray tracing techniques along with machine learning and deep learning to produce more precise results.

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