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# A Review of Comparative Study on Path Loss using Machine Learning Algorithms

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## ABSTRACT

***Radio Frequency need to be utilized efficiently as it is a natural limited resource. Electromagnetic waves arrive at the mobile station from different directions through different terrains with different polarization and time delay. To determine the coverage of a cellular network, it is necessary to use effective propagation models. The RF survey plays an important role to know the primary user's activities at a particular geographical location. In this paper a comprehensive survey of various models used for path loss detection are discussed. This survey involves several papers comprising the research direction to find the performance of path loss models using Machine learning (ML) algorithms.***

**KEYWORDS:** *Radio Frequency, RF Survey, Mobile station, Machine learning, Terrains, Cellular network.*

## INTRODUCTION

Electromagnetic waves arrive at the mobile station from different directions through different terrains with different polarization and time delay. Therefore, receiver far away from the transmitter will receive the power different than the receiver kept near to the transmitter. As the movement of mobile changes with respect to time, it may experience fluctuations in phase and amplitude. In this case, signals may get affected due to fading.

To determine the coverage of a cellular network, it is necessary to use effective propagation models. Empirical models are the popular propagation models that helps to determine the location of site to choose optimum position in the network. The probability of choosing incorrect site can be high if the path loss model is not effective in providing correct estimation. As the model can be used for interference prediction, the performance of the network can be affected.

The ultimate objective of RF surveys is to provide the detailed study and coverage over the terrain. Before implementation and optimization of a wireless network, an RF Engineer wants to know about the possible interference area, placement of access points,power levels consideration and fixed wire needed for the same. A wireless survey can provide the above information all together.

The process of predicting RF survey does not need field measurements. One can prefer software for RF planning that can predict the RF coverage of access points. For that a drawing of floor-planning is necessary.

Generally, predictive site survey is useful when building is not yet built and it helps in budgeting of the network.

The problem of prediction of path loss is frequently occurs in the wireless network planning. Machine learning algorithms plays very important role in predicting not only path loss but also coverage area, frequency etc. Yan Zhang [1], has shown the comparative study of various Machine learning algorithms viz. Back Propagation Neural Network (BPNN), Support Vector Regressor (SVR), Random Forest, k-nearest neighbor shown that accuracy of SVR is better than rest of algorithms. Especially supervised learning, can model hidden non-linear relationships and thus can be used for path loss prediction. It has been shown that machine-learning-based models, including ANN, SVR, and Random Forest, are in good agreement with measured data and applied for the path loss prediction.

Sridhar Bolli et.al [2], explains Perez-Vega Zamanillo model and comparison with standard path loss models proved that it was more accurate for Indian geographical region. Here survey conducted in major metropolitan cities in UHF/VHF band and considering only RMSE as performance parameter. The author shown the development and optimization of a path loss model based on Linear minimum mean square error estimation (LMMSE) for India.

M´onicaRibero[3], This research work implemented different neural network architectures with dense and convolutional layers that could include effects difficult to describe with traditional models. Here 8 dB improvement achieved compared to traditional slop intercept solutions. CNN model was found to be better compared to intercept solution and traditional neural network as it shows 4.9 RMSE even though it takes 6 minutes and 787K parameters.

M. Piacentini[4], This research work talks about combination of learning machines and dimensionality reduction techniques. The goal of Dimensionality reduction is to transform input data into a reduced representation set of features, while keeping as much relevant information as possible. The results show the efficiency of learning machine on real data sets. The ANN regression yielded slightly better results than the SVM classifiers. The prediction accuracy has been improved using real time dataset.

N. Kuno in his article[5] shows the effect of Deep Learning technique on path loss prediction model. Convolutional Neural Network (CNN) model has been used to characterize the path loss while considering effects of obstacles in environments.Danilo Erricolo,[6] obtained the results from empirical models like COST-231Walfisch-Ikegami, Hata's, and Zhang's model are compared with the 2D propagation model in an urban area.

## 2. Role of Machine Learning (ML) in RF survey

The traditional path loss predictive models like Hata, Okumora, longly-Rice Bulling-ton, Egli etc. have been built based on empirical and deterministic methods. Empirical models work with simple parameters and model equations are concise. However, the parameters are extracted from a measured data set in a specific scenario. Therefore, shows less accuracy when applied to general environment [7]. Also, empirical models represent only statistics of path loss at a certain distance, and cannot predict the power level at a specific geographic location.

Ray-tracing and finite difference time domain (FDTD) are the deterministic models. These models apply radio wave propagation mechanism and numerical analysis to model the electromagnetic computations. They can provide the higher accuracy and path loss value of any specific position. The major disadvantage of deterministic models is that they are lack of computational efficiency. Geometry details (location specific) and dielectric properties are also required for the operation. Also, if the propagation environment has changed, we have to run the time-consuming computation again.

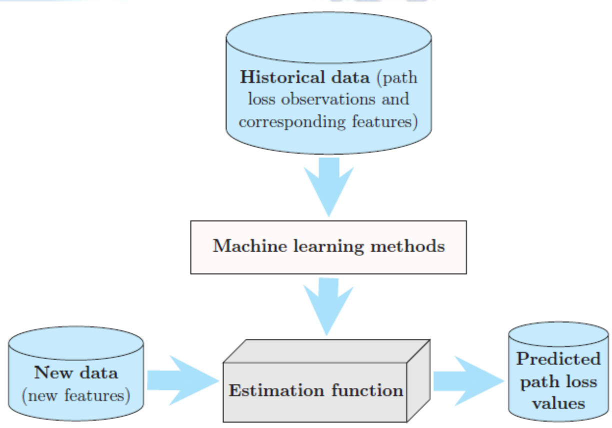


Fig.1. Machine learning estimation process

*Machine learning (ML) allows the determination of base location without extensive exercise RF field measurements. ML models are data driven and effective as compared to conventional propagation path loss models like empirical, deterministic and semi-deterministic. The Machine Learning models have flexible architectures to make pre-dictions. The generalized operation of Machine Learning models is as depicted in figure 1. The path loss can be predicted using historical data and estimation function.*

Machine learning based models are used to predict the path loss, link quality, RSSI in complex terrain. This helps to know about the spectral traffic information. Theinformation about the activities of licensed users are the vital aspects in case of smart Radios like Cognitive Radio. The spectrum sensing is an important stage in Cognitive Radio operation. The RF data can be captured from the electromagnetic environment.

Prediction of propagation path loss can be defined as a regression problem. Machine Learning tools are useful to solve regression problems and can be efficiently applied to obtain a reliable solution to wave propagation prediction model (1995, Balandier et.al.;1998, Fraile and Cardona; 1997, Yang and Chang; 1996, Landstorfer and Gschwendtner; 2002, Popescu et.al.). The regression models are fully function of the datasets and training to the model. Irrelevant and redundant data should be avoided while training the regression model. To improve the conventional regression prediction model, dimensionality reduction approach is useful [4]. Figure 2 shows the process of path loss prediction using three input parameters. The information like Rx configuration, Terrain details and frequency can be the input to the predictive model.

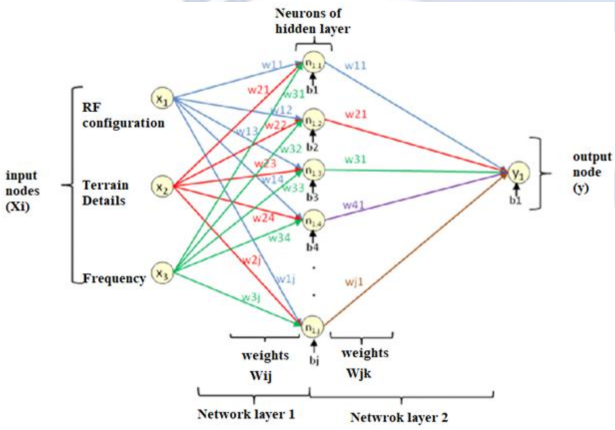


Fig. 2. Artificial Neural Network architecture for pathloss

The objective for the model would be to get path loss prediction f(x) using dimensionality reduction techniques and machine learning algorithms that gives best estimation of path loss.

## 3. Popular ML models used for path loss prediction

Most of the research work [1],[3],[4],[5] used the Machine Learning algorithms to justify the data and verify the performance of the path loss prediction models. The model can be based on techniques like Artificial Neural Network (ANNs), Support Vector Machine (SVM), decision tree, Random Forest, K-Nearest Neighbor (KNN) etc. Some Deep Learning methods like Convolutional Neural Networks have also preferred for path loss prediction. Machine learning algorithms are classified into two major categories. Supervised and unsupervised algorithms. In supervised method, the objective of the method is to learn the accurate function between input and output that make it suitable for regression and classification problems. Unsupervised algorithms have to describe the unlabeled data. From the observation, one can say, path loss prediction is a supervised regression problem which can be solved using Machine learning algorithms. It is found that machine learning based models are more accurate than traditional empirical and deterministic models [8],[9].

a) Artificial Neural Networks:

Artificial neural networks (ANNs) are adaptive statistical tools that model the way biological nervous systems, such as the brain, process information. Generally, ANNs consist of several elementary processing units called neurons, which are located in different layers and interconnected by set of weighted edges. As mentioned above, path loss prediction can be done using any supervised learning algorithm. An artificial neural network shown in figure 2 indicates the basic neural structure consisting of input layer, hidden layer and output layer. Input layer consists of three nodes indicating input parameters like RF configuration, Terrain details and frequency.

Input nodes in input layer are connected with each node in hidden layer. Eachconnection between nodes is weighted Wij like neural networks present in human brain showing the active connections. The suffix i shows number of input nodes and j indicates number of nodes in hidden layer. Output has only one node giving output y. Nodes in hidden layers consists of activation functions for producing the meaningful data at the output node. Generally, the activation functions preferred in neural model are sigmoid, tanh and ReLu.Following equations shows the activation functions.

$$\text{Sigmoid } f(x) = \frac{1}{1+e^{-x}} \quad (1)$$

Where, x is input to sigmoid function. The function gives output in the range 0 to 1. Hence the input length must be set accordingly.

$$\tanh f(x) = \frac{1-e^{-x}}{1+e^{-x}} \quad (2)$$

Where, x in input sample to tanh function. The function gives output in the range of –1 to1. So, the input data sequence should be adjusted before applying to tanh function in neural model.

$$f(x) = \max(0,x) \quad (3)$$

The ReLu function is the most commonly used activation function in deep learning. It returns 0 if it receives any negative input, but for any positive values, it returns that value back.

Back propagation Neural Networks (BPNN) is a low complex method used to train the ANNs. Let the given set of inputs is $\{(x_1,y_1),(x_2,y_2),\ldots\ldots(x_n,y_n)\}$, where, $x_i = \{x_1^i, x_2^i, \ldots\ldots x_n^i\} \epsilon R^L$ is a feature vector, and $y^i \epsilon R^1$ is the target output, measured value of path loss. In forward propagation phase the predicted value of path loss $y'_i$ can be expressed as

$$y'_i = f_{out}(\omega_{out}(f_h(\omega_h x_i) + \theta_h)) + \theta_{out} \quad (4)$$

where, $\omega_h$ is connection weights between input and hidden layer neurons, $\omega_{out}$ is connection weights between hidden and output layer neurons. $\theta_h$ and $\theta_{out}$ are thresholds of the neurons of hidden layer and neurons at output layer. $f_{out}$ (.) and $f_h$(.) are transfer functions for hidden and output layers.

Neural Networks can be categorized into four architectures viz. feed forward, Recurrent, Hybrid and emerging methods. First type of architecture is feed forward which is basic structure that deals with only one way information transfer (generally from left to right). There would not be weight updates in this type. Neural networks like multilayer perceptron (MLP), Radial Basis Function Neural Network (RBFNN), General regression neural networks (GRNN), wavelet neural networks (WNNs), Cascade correlation neural network (CCNN), Modular neural networks (MNNs), Time Delay Neural Networks (TDNNs) are the different feed forward neural networks. Second type of neural networks are preferred due to gradient descent problem, the next advancedand complex architectures of neural networks are preferred know as Recurrent Neural Networks (RNNs). Long Short-Term Memory (LSTM) is one of the complex architectures having memory to store the output of previous iteration. The other types of recurrent neural networks are Nonlinear Autoregressive with exogenous input (NARX), SRU, Time-lag recurrent network (TLRN), Echo state network (SEN), Ridge regression echo state network (RESN).

Hybrid types of neural nets are structured on the three different intensive methods. First one is Model intensive type like fuzzy wavelet neural network (FNN-WNN) and another is LSTM-RNN. Second type of hybrid network is technique intensive i.e. ARIMA- RBFNNs, ARIMA-ANN. Third is data intensive includes wavelet ANN, principal component analysis (PCA) with back propagation (BP) neural networks, k-means multilayer perceptron, empirical decomposition (EMD)-BPNN, practical swarm optimization (PSO)-BPNN.

New emerging methods have significant impact on the predictive models. Convolutional neural network, specially used for image data found many applications in bio-medical imaging, descries predictions, classification. The problems like detecting cancer with the help of historical data can be solved using deep neural networks.

| | |
|---|---|
| Feed forward | MLPs, RBFNNs, GRNNs, ELMs, Wavelet neural networks (WNNs), Cascade correlation neural network (CCNN), Modular neural networks(MNNs), Time Delay Neural Networks (TDNNs) |
| Recurrent | RNN, LSTM, Elman, Nonlinear Autoregressive with exogenous input (NARX), SRU, Time-lag recurrent network (TLRN), Echo state network (SEN), Ridge regression echo state network (RESN) |
| Hybrid | **Model intensive:** e.g. fuzzy wavelet neural network (FNN-WNN), LSTM-RNN<br>**Technique intensive:** e. g ARIMA-RBFNNs, ARIMA-ANN<br>**Data intensive:** e.g. wavelet ANN, principle component analysis with back-propagation networks (PCA-BPNN), K-means-MLP, empirical mode decomposition (EMD)-BPNN, particle swarm optimization (PSO)-BPNN |
| Emerging methods | CNN, Deep belief network (DBN), Self-organizing deep belief network (SODBN) |

Fig. 3. Summary chart of Artificial Neural Networks

Since its inception, artificial neural network has been preferred as one of the choices among the researchers. Figure 3. Provide a summary chart of Artificial Neural Networks. Perceptron neural networks are feed forward type basic building blocks which helps for building simplified solutions to the prediction problems. The major drawback of feed forward neural network is that it cannot update the weights to optimize the performance of neural model. To overcome this problem, back propagation neural networks have been invented that has ability to update the weights after each iteration. A Simple back propagation neural network (BPNN) had a problem with gradient descent. As the problem with BPNN was to optimize the performance of neural model based on minimum error between actual data predicted data. Recurrent neural networks over comes this problem of gradient descent by applying iterative method and storing the data from previous stage in memory.

There has been tremendous work on prediction of path loss using different methods. Figure 4 shows the trends in various methodologies used to path loss prediction. Among these methodologies, Artificial neural network found the most preferred choice with 39.1% utilization during 2004 to 2019.

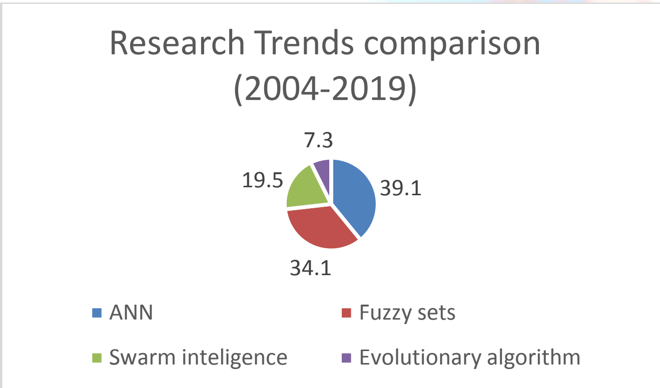


Fig. 4. Research trends during 2004-2019[10]

b) Overview of Machine Learning algorithms:

In [11], Zhang has depicted the K-Nearest Neighbor and Random Forest (RF) for path loss prediction in urban surroundings for Unmanned Arial Vehicle (UAV) communications. Machine learning based models have comparatively high prediction accuracy and acceptable computational efficiency. Support Vector Regressor can be used in path loss prediction in semi urban area. [12,13]. Algorithms like tabu search and genetic algorithms have been used to make predictions for SVR-based model. A predictive model for in cabin path loss values had been developed at 3520 MHz which performs better than curve fitting model [14]. An efficient model based on SVR had been developed for getting good accuracy with acceptable computational cost [15].

## 4. Mechanism of RF survey

i) Methodology RF survey

Wireless survey of a certain premises can be defined as a physical investigation of the area where wireless network will be installed. The survey report shows the records of coverage area and data rates. The tools used in RF survey can be handheld spectrum analyzer to measure signal strength and interferences. Some predictive tools that use the building floor plans and wireless node proposed locations to predict the coverage mathematically instead of using actual measurements.

ii) Different Terrain for ML models

There are various terrain types for which one can do the RF spectrum survey and model the path loss prediction. The other parameters like the status of primary user traffic, coverage, utilization of frequency, received signal strength (RSSI) can be considered to check the performance of predictive model. These field parameters vary as the terrain type.

Many pathloss predictive models build for urban environment represent building obstructions using knife-edge approximation mentioned in [16] – [21]. The knife-edge approximation is one of the simplest waysto model a building obstruction. But the greatest disadvantage is that it limits the actual situations [22]. The knifeedge approximation is still a widely used method for buildings.

iii) Crowded urban area

It has been found that predictions using Machine learning algorithms are more suitable for crowded urban area. Even though the urban area is densely populated, terrain with tall buildings and trees, the machine learning based predictive models gives more accuracy and less predictive errors compared to empirical and deterministic models.

iv) Pros of Machine Learning algorithms

Machine learning is found to be the useful tool in building propagation model to find the path loss prediction for various type of terrain. The ML models produce a very good results on real time data sets. ML model can be effectively applied to obtain a dependable prediction of wave propagation.

## 5. PERFORMANCE PARAMETERS OF PREDICTIVE MODELS

In order to verify the performance of predictive models, it is necessary to access the models with the help of performance parameters. These parameters can be categorized into major two types, Field parameters and algorithmic parameters.

**a) Field parameters** (path distance, RSSI, canopy coverage, terrain variability, and path angle): Machine leaning can be used to determine the field parameters like Traffic prediction, Traffic classification, Traffic routing, Congestion control, Resource management, Fault management, QoS and QoE management, Network security. These field parameters can be considered as features of the data sets. The field measurement data can be used to process through the neural models and make the path loss predictions. Path loss predictive models are evaluated by root means square error (RMSE) given by equation 5.

$$RMSE = \sqrt{(\sum (P_m - P_{pred})^2 / n} \qquad (5)$$

Where, $P_m$= measured path loss, $P_{pred}$= predicted path loss, n= total number of measured data points. One can access the model performance using other parameters like mean square error (MSE).

**b) Algorithmic parameters** (MSE, RMSE, MAE): While implementing neural models for path loss prediction, it is necessary to evaluate the model based on certain parameters that gives periodic / aperiodic results. The parameters like average error, standard deviation, Mean Square Error, Root Mean Square Error performs the significant role in prediction process. Lesser the difference between predicted and actual data points, higher the accuracy of the model. The equations used to find the errors can be defined by (6), (7) and (8).

$$err = P_m - P_{pred} \ (6)$$

Where, err is difference between predicted and measured values.

$$MSE = \sum_1^n (err)^2 / n \ (7)$$

Where, MSE is mean square error, n is total number of input data points.

$$MAE = \frac{\sum_1^n | y_k - x_k |}{n} \ (8)$$

Where, MAE is mean absolute error, $y_k$ are predicted data points, $x_k$ are actual data points.

## 6. SUITABILITY OF MACHINE LEARNING ALGORITHM FOR CROWDED AREA

Path loss prediction is one of the crucial tasks in today's modern cellular network. Machine learning is considered to be a very good alternative to the empirical and deterministicmethods in the path loss prediction. In the smart wireless communication system, Machine learning models plays a role of highly efficient predictor. ML models are used to predict the path loss, RSSI, coverage and many more parameters. ML models have many comparative advantages over empirical, canonical and deterministic models.

## 7. METHODOLOGY

The methodology followed by all Machine Learning algorithms is as mentioned in figure 5.

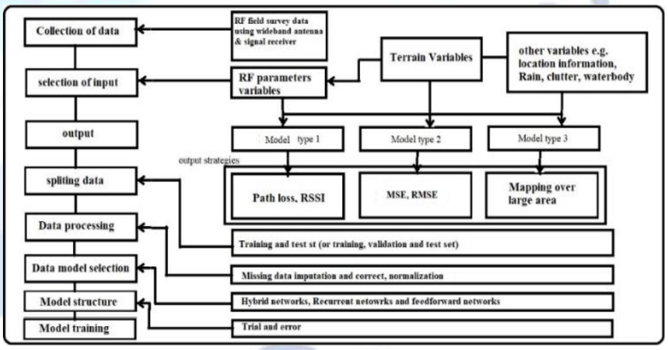


Fig. 5. Methodology followed by Machine learning algorithms

Data needs to be collected from the field area that is counted in training the ML models. The input dimension would be decided based on the dimension of total dataset, processing units of the training model and the expected output. Following steps elaborate the complete cycle till the training of the ML model.

a) Collection of Data:

The collected data should include the path loss values and input features. The RF data has been collected from the RF wideband antenna, signal receiver in terms of Received Signal Strength. The features in the dataset can be divided into two categories. System dependent parameters and environment dependent parameters. System dependent parameters like carrier frequency, heights and positions of the transmitter and receiver etc. Environment dependent parameters are like terrain, building condition and vegetation condition. The performance of path loss model is closely associated with the number of samples in training data set. The complete data can be divided in to training and testing data sets. The former is preferred to prepare the prediction model; however, letter is used to verify and to improve the performance of the model.

b) Selection of input:

The input to the ML model depends on the RF information, terrain information or other variables like location information, rain, and clutter or water body. The input is selected based on the requirement of prediction.

c) Output:

The Machine Learning models can be evaluated using various parameters. The predictions from the ML models can be in terms of path loss, RSSI, Mean Square Error, Root Mean Square Error and the mapping information over larger area. These models can be trained for different purpose and the duration. The data processing in the models can be done using split method. The input data can be divided into training and testing data sets or training, validation and test datasets. Sometimes training and test data is sufficient for the model to produce the output. Sometime the model needs validation data to validate the model after successful training.

d) Model Selection:

This is one of the difficult tasks to select the appropriate model for the prediction process. As discussed, the predictive model can be based on the three types viz.hybrid networks, recurrent networks or feedforward networks. The neural models are the most preferred models in data analytics.

e) Model Structure:

Based on the different requirements, data input and processing through the model, the structure could be decided. Most probably trial and error method is used to select the structure as the efficiency of models varies with model architecture. Neural structures are popular among the researcher community.

**Table 1. Evaluation of performance of propagation models (For American River Hydrologic Observatory (ARHO)) [23]**

| Model used | Average Error (dBm) | Standard Deviation (dBm) |
|---|---|---|
| Free Space Model [24] | 20.5 | 8.60 |
| Plane earth[24] | 17.8 | 6.92 |
| Weissberger [25] | 6.65 | 4.70 |
| ITU-R[26] | 6.37 | 4.64 |
| COST235[27] | 5.91 | 4.37 |
| Random Forest[23] | 3.72 | 3.41 |

Table 1 shows the comparative study of various empirical models with Random Forest algorithm interms of average error and standard deviation represented in [23]. It is very clear that, machine learning which is data base driven, has shown significantly good results. It shows lowest average error and standard deviation compared to all empirical models.

## 8. CONCLUSION:

The review of machine learning algorithms for path loss prediction found that Machine learning models are far better than traditional predictive models. The inability of getting detailed information about the propagating environment leads to the more intelligent algorithms to predict the path loss. Artificial neural networks (ANNs) and fuzzy systems are the perfect examples of such algorithms. ML models are better because they are adaptive to the changes in environment and produce the comparative better predictions.

**Conflict of interest statement**

Authors declare that they do not have any conflict of interest.

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