Signal Strength Extrapolation after Crossing an Urban Area

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Free space wireless signal communication has the capacity and vast spread expansion to provide the right platform to support the growing demand for communication services. The propagation of electronic waves is the core of actual wireless communication links between ground stations and satellite ground communications. However, rain, dust, ground topography, urban surface, and other physical barriers weakened the transmitted signal strength and loss, reducing the quality and completion of the data transfer process. This work focuses on diffraction, weakening, and loss of signals when crossing urban areas surrounded by high buildings. We present a machine learning model for estimating the signal strength after crossing the urban areas. This assessment helps recommend the proper signal strength required when launchingthe signals towards the end station located in urban surroundings. We use aneural network system that derivespatterns and rulesfrom a given dataset containing simulated sampling data and predicts the optimal transmission strength when launched.

Keywords: Wireless communications, Urban area communication station, Signal weakening, Machine learning.

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1. Introduction

Wireless communication services became attractive to mega-companies that foresee an excellent opportunity to connect disconnected remote regions, serve emerging machine-to-machine communication, Internet-of-things connectivity, etc. Typical ground stationsinmodern urban areas are surroundedby high buildings disturbing the propagation of electromagnetic waves. This research focuses on the reflections and diffraction signals caused bybuildings, leading to reduced signal effectiveness and even signal loss. To avoid this, it requires increasing the signal strength accordingly. Predicting the signal attenuation and correcting the transmission intensities make it possible to maintain a proper signal-to-noise ratio (SNR) and prevent transmission interference.

Some research proposalsoffer a variety of assumptions and tailored solutions. Some focus on rain and dust,while others provide estimated measures for signal propagation through buildings built from various materials, such as concrete, wood, and metal. We propose a machine learning-based system that accurately estimatesthe signal attenuation level and automatically increases the next signal strength. We have developed a prototype using Machine learningand associated Python programming software. Then we conducted fiveexperiments, one for each frequency from 2.4GHzto 72GHz, using data collected from a satellite belonging to the Genesis project. Results show that the estimated signal for all frequencies is close to the actual value.

This paper is organized as follows: section 2outlines related work, section 3 presents the proposed model, section 4 outlines the experiment setup and results, and section 5 contains the conclusions and future work.

2. Related Work

Tozer et al. [1] Outline the application and features of High-Altitude Platforms (HAP) for Wireless Communications and consider using HAPs to deliver future broadband wireless communications. The term building entry loss we used here corresponds to the definition made at ITU-R Rec. [2], defined as the excess loss due to building walls and other building features. Building entry loss depends on the building type, construction, and electrical parameters of the material used. Measurements of Penetration loss of various building materials at 1–8 GHzappear in [3]. [4,5] presentelectrical parameters of materials of S-band frequencies. Many other aspects influence the building entry loss, such as the receiver's position inside the building, the elevation of the transmitter, and so forth, making it difficult to estimate the level of received power inside a building accurately. Adecrease in the entry losses into building with floor height can often be observed [6,7]. Entry loss measurements for2 GHz arereported in [8,9]. Measuring the spread of the received signal within buildings has been reported in [10,11, 12]. In [13], the authors focused on the overall building entry loss and building entry loss as a function of elevation and entry angle and the results of time delay spread. [14]presented a new model of the path loss parameters.D. Micheli et al. [15] describe a simple way to measure electric wave attenuation within an indoor scenario, demonstrating attenuation level differences for different wall materials and textures. Al-Hourani et al. [16] propose a framework for modeling satellite-to-ground signal attenuation in urban environments.It captures the shadowing using measurements collected from a global navigation satellite system (GNSS).The mentioned methods are based on various data analysis methods to identify the contributing parameters to signal loss. This approach requires proof of the truth of the found parameters. Our proposed system is based on accumulated data processed by proven ML methodologies generating improved and accurate outcomes.

3. Experiment Background, Setup, and Execution

Building shadowing loss relates tothe transmission loss through a building. Measurements have been formulated to calculate values ofbuilding shadowing loss. For example, the average loss through concrete/brick building fora frequency of 11 GHz. with vertical and horizontal polarization is 30.1 dB

(Std. dev. 5.0) for V-Pol and 28.6 dB (Std. dev. 5.5) for H-Pol.These measurements show a highdependency on construction material in determining the primary propagation mode and the amount of attenuation caused by the obstacle. Metal-based construction buildings generate the highest average signal attenuation, 35-40 dB. Concrete causes 25-35 dB, and wood 10- 25 dB. The transmission was the main propagation mode for wooden and concrete structures. Propagation by diffraction appears for metal, increasing from the corners towards the center of the building shadow. The attenuation due to diffraction increased from 5.0 to 10.0 dB.

The free space loss formula is as follows:

$$L_{fs} = 32.45 + 20 \cdot log(d_{(m)}) + 20 \cdot log(f_{(GHz)}) \quad (1)$$

Where ***d*** is the distance defined in Fig. 2. and ***f*** is the carrier frequency (GHz). Set transmitted power to be ***Pt***(dBm) and received power to be ***Pr***(dBm). The losses through the Buildingarestated as $\boldsymbol{L_E}$, sending antenna gain, and receiving antenna gain in the transmission path are denoted as G_T and G_R, respectively.Then we can get equation (2):

$$P_{t(dBm)} + \left(G_t - L_{fs} - L_E + G_r\right) = P_{r(dBm)} \quad (2)$$

And then, the losses through the Buildingare inferred from equation (3).

$$L_E = \left(P_{t(dBm)} - P_{r(dBm)}\right) - L_{fs} + (G_t + G_r) \quad (3)$$

The Omni-directional antenna used in the experiment is likea half-wave dipole antenna whose gain is 2.15 dB, and the normalized directivity function of the electric field of the half-wave dipole antenna is presented by equation (4):

$$F(\theta) = sin(\theta) \quad (4)$$

From equation (4), we get equation (5):

$$G_t + G_r = 4.3 + 10 \cdot log([F(\theta)]^4) = 4.3 + 10 \cdot log(sin^4\theta) \quad (5)$$

The horn antenna is the receiving antenna in the building scenario, so the receiving antenna gain is appropriatelyconsidered.

We selected a reinforced concrete shear wall structurebuilding. The antenna is a horn antenna with vertical polarization, and the transmitter is an Agilent E8267D signal generator. The output power in the test is set to 33 dBm, and the receiver is an Agilent N9030A signal analyzer.

For Constructing the database for the learner,we used the collected data based on: (1) the building loss, (2) geometric calculations related to the location of the ground station and the height of the building, (3) and Satellite orbits to build a learning database that will enable building loss prediction. The input data came from STK simulation, which links satellite orbit (time and angle) with channel orientation, and geometric calculations relating to a particular scenario.Table 2 depicts an example of the database record layout used for our experiment with a signal frequency of 72 GHz:

Table 1: Dataset records used for our prediction experiment

Time (LCLG)	Azimuth (deg)	Elevation (deg)	Range (km)	EIRP (dBW)	Xmtr Power (dBW)	Xmtr Gain (dB)	Xmtr EIRP Intensity (dBW/Sterad)	Atmos Loss (dB)	UrbanTerres Loss (dB)
24/6/2020 12:18:20	269.08	5	2092.57019	84.8873	30	126.7933	73.7783	17.4649	243.72
24/6/2020 12:18:21	269.082	5.048	2088.404155	84.7149	30	126.6204	73.6948	17.3154	243.09
24/6/2020 12:18:22	269.086	5.124	2081.760992	84.6428	30	126.4718	73.5434	17.0813	242.39
24/6/2020 12:18:23	269.09	5.201	2075.118627	84.5081	30	126.3504	73.475	16.8524	241.64
24/6/2020 12:18:24	269.094	5.278	2068.477073	84.3521	30	126.2628	73.3019	16.6285	241.02
24/6/2020 12:18:25	269.098	5.355	2061.836346	84.2634	30	126.1509	73.2396	16.4095	240.32
24/6/2020 12:18:26	269.102	5.432	2055.196461	84.1542	30	126.0643	73.114	16.1952	239.76
24/6/2020 12:18:27	269.106	5.51	2048.557434	84.102	30	125.9682	72.9149	15.9854	239.08
24/6/2020 12:18:28	269.11	5.588	2041.919281	83.91	30	125.8196	72.7792	15.7801	238.46
24/6/2020 12:18:29	269.114	5.666	2035.282017	83.8062	30	125.6988	72.697	15.579	237.76
24/6/2020 12:18:30	269.118	5.745	2028.645659	83.7767	30	125.6444	72.688	15.3821	237.21
24/6/2020 12:18:31	269.122	5.824	2022.010222	83.7702	30	125.5029	72.4907	15.1892	236.62
24/6/2020 12:18:32	269.126	5.903	2015.375724	83.5991	30	125.3556	72.3137	15.0002	236.06

This database will serve for training the deep learning system described in the next step. Above the table header is the source of each table column.

For the prediction method, deep learning (DL) algorithm has been developed, with the following steps:

1) *Accept the training and experiment dataset*

Table 2 is an example of the training and experiment data set required to input the predicting system.The label class in this case can be binary (e.g., **+1** (if attenuation = 0), **-1** (if attenuation ≠ 0)).

2) *Execute the Prediction deep learning algorithm*

The following notation demonstrates the prediction procedure:

$$X_{m \times n,d,t} \rightarrow Y_{m^* \times 1,d,t+\Delta t}(train\ file) \quad (6)$$

$$X_{\tilde{m} \times n,d^*,t} \rightarrow Y_{\tilde{m}^* \times 1,d^*,t+\Delta t}(experiment\ file) \quad (7)$$

*X*represents samples of satellite data, with matrices size $m \times n$ produced at a specific date d and specific time t with class labels m^* produced for the same date d but with different time $t+\Delta t$). The trained classifier classified the experiment samples (made from latterly date d* and specific time t). Because the algorithm classifier labels for future times, it is a prediction of satellite attenuation.

Satellite data may vary according to days and time (hours/min/sec). This section will denote by $X_{m\times n,d,t}$ a dataset of size m with n features, collected on day d and at time (hour/min/sec) t and by $Y_{m\times 1,d,t}$ the class labels associated $X_{m\times n,d,t}$. Therefore, the prediction problem is given a dataset $X_{m\times n,d,t}$ known for every time t to estimate $Y_{\tilde{m}\times 1,d+\Delta d,t+\Delta t}$, where Δd and Δt respectively define a variation of day and time (hour/min/sec).

The proposed estimation procedure then can be decomposed into four steps:

i. Collect two samples of data, $X_{m\times n,d,t}$ and $X_{m\times n,d,t+\Delta t}$, $\Delta t > 0$,

ii. Compute the class labels $Y_{m\times 1,d,t+\Delta t}$,

iii. Compute a new training set $Z_{m\times n+1,d}$, using $X_{m\times n,d,t}$ and $Y_{m\times 1,d,t+\Delta t}$ by concatenation, that is $Z_{m\times n+1,d} = [X_{m\times v,d,t}; Y_{m\times 1,d,t+\Delta t}]$,

iv. Collect the test set $X_{\tilde{m}\times n,d+\Delta d,t}$ ($\Delta d > 0$), and compute $Y_{\tilde{m}\times 1,d+\Delta d,t+\Delta t}$ using the machine learning algorithm on $Z_{m\times n+1,d}$ and $X_{\tilde{m}\times n,d+\Delta d,t}$

The learning system that predicts the channel attenuation is trained. Two different methods are used to find a faster and more accurate process. We use the MLNN (long short-term memory) model. It is an artificial neural network designed to recognize patterns in data sequences, such as numerical time series data emanating from sensors, stock markets, and government agencies. RNNs (recurrent neural networks) and MLNNs are different from other neural networks as they have a temporal dimension.

We aim to maintain a constant signal level conveyed by the desired SNR level for system alignment, which may differ from the predicted signal-to-noise ratio level. We use the following model:

$$SNR_{predicted} - SNR_{Desired} = 0 \rightarrow \frac{P_T \cdot G_T \cdot G_R \cdot L_{FS} \cdot L_E}{N_0 \cdot B} - SNR_{Desired} = 0 \quad (8)$$

where $\boldsymbol{P_T}$ is transmitter output power, $\boldsymbol{L_E}$ is losses through the Building, $\boldsymbol{L_{FS}}$ is free space path loss, $\boldsymbol{G_T}$ is the transmitting antenna gain, $\boldsymbol{G_R}$ is the receiver antenna gain,***No*** is noise energy, and ***B*** is the bandwidth. Using the parameters $\boldsymbol{P_T}$ and $\boldsymbol{L_E}$, we achieve this goal. If the losses through the buildingdecrease, the transmitter outputsthe power required to adjust and vice versa.

The experiment setup comprises a neural network system, a Pythonprogram code, and sample records described in section 3.5. We have built a system that assesses SNR values for a future timeframe. The model succeeded in predicting the SNR sample one second in advance, based on the samples with a loss of 1%, which is still reliable. We collected data from satellites, researched and explored optimal ways to build the deep neural network architecture, and chose the parameters which reduce the loss function to a minimum. The MLNN system comprises two stages. The first is building, loading the neural network, training, and testing the received input data. The second stage is analyzing a prediction of the intensity of the signal for the concise term. The mechanism comprises several epochs, starting with the entire input samples, reducing to a smaller number, and reducing to one instance at the final stage.We identified the optimal parameters converged after four epochs. The parameters are a. Loss function: mean absolute error, b. Optimizer: "Adam", c. Activation function: “tanh”, d. Number of epochs to saturation: 4, 3 layers: 2 MLNN,1 Dense - First layer: 98 neurons, Second layer: 20 neurons, Last layer:1 neuron.

4. Results

We introduced the Machine-learning process and compared the predicted attenuation levels to the actual results executed over variousfrequencies, from 2.4GHz to 72GHz. The experiment started with training the MLNN system using 913 sample records from the STK satellite simulation connected to its corresponding earth station.We performed a separate investigation for each of the five frequencies.In all experiments, the difference between the estimated signal loss Vs. the actual loss is very close. We checked the training results, and they resemble the accurate results to a convincing extent.

5. Conclusions

This workexploresthe accuracy of a Machine Learning Neural Networks model to predict the signalattenuation while signals propagate via the free space, disturbed by rain, haze, and dust.We executedour system for the following frequencies 2.4GHz, 10GHz, 23GHz, 48GHz, and 72GHz. We compared the predicted and actual results and found that our prediction model isclose to the actual results. The accuracy level of the Neuron Network is very high. In future work, we intend to improve prediction accuracy further, expand the research applicability to other obstacles causing signal attenuation and loss, and propose the proper formula or mechanism to overcome these obstacles.

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