Machine Learning-Based Rain Attenuation Prediction Model

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Abstract. Rain attenuation is an important factor affecting wireless communication systems throughout the world. Rain attenuation and rain rate data are collected using multichannel radiometer and laser precipitation monitor at a tropical location. The dataset obtained is used to initially propose an empirical model for prediction of rain attenuation from rain rate data. An alternative model using linear spline regression-based machine learning is also used to predict rain attenuation. The machine learning-based model is found to be more accurate by an appreciable degree compared to the empirical model proposed in the previous instance.

Keywords: Rain attenuation · Multichannel radiometer · Empirical model · Linear spline · Regression · Machine learning

1 Introduction

Attenuation of communication signals due to rainfall is a significant parameter that affects terrestrial and satellite communication links worldwide. Different methods of measurement and estimation of attenuation are employed by researchers at present. The effect of rain attenuation is especially felt in the tropics due to the concentration of the major amount of global rainfall in that region of the world [1]. In fact, majority of the efforts have been made during the last decades to characterize the statistical and dynamical aspects of rainfall rate and subsequent attenuation at the desired frequencies in the earth-space path. The physical approach to predict rain attenuation is to calculate the path attenuation through an integral of all the individual increments of rain attenuation caused by the drops encountered along the path [2, 3]. However, since the rain cannot be accurately described along the aforementioned path, all proposed models are empirical in nature.

The present paper outlines a machine learning-based estimation approach to predict rain attenuation at multiple frequencies. The paper is divided into the following sections. The succeeding Sect. 2 outlines some of the relevant research in the domain of estimation of rain attenuation through empirical models. Section 3 briefly discusses the instruments used for measurement of rain rate. Section 4 presents the empirical model initially

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proposed in the paper and then introduces the machine learning-based linear spline regression model which gives a more accurate estimate than the previously introduced curve fitting model. Accordingly, results obtained using both models are presented in comparative fashion in this section. Section 5 then concludes the paper with a brief discussion on future avenues of research.

2 Literature Survey

Extensive rain attenuation data collection has been carried out for temperate regions, where the trends displayed by such datasets do to occur in other regions with comparatively more rainfall, such as tropical regions [4]. Generally, in these regions, rain is mostly of stratiform structure, which is 'light' with relative large rain cell diameters [5]. But in tropics, rain is at times from convective rain cells with relatively small diameter which often results in heavy down pour for a short period [6]. However, different types of rain show different types of spatial structure, and hence, the vertical path is affected differently in the presence of stratiform rain and convective rain [7, 8]. Rain attenuation at high frequencies for 5G applications has also been investigated in recent years [8]. Previously proposed methods of calculation of rain attenuation have been shown to be less reliable under certain rainy conditions [9]. Specific rain attenuation is especially variable, as can be seen in recent works by researchers [10]. It has also been observed and reported by certain scholars that rain rate variations may cause loss-of-lock in communication and navigational systems [11].

As a consequence to the importance of rain attenuation measurement, machine learning models have been extensively used by researchers in recent years [12, 13]. Machine learning tools such as neural network-based models have become popular among researchers in recent years due to their accuracy [14].

The present paper therefore proposes a machine learning-based approach for predicting rain attenuation and investigates the efficacy of such an approach through comparison with other estimation models as well as actual values of the variable.

3 Measuring Instruments

Radiometer and laser precipitation monitor are used to collect data. The features of the radiometer and laser precipitation monitor are outlined in brief.

The radiometer used is a radiometrics profiling radiometer. This radiometer (MP-3000A) series incorporates two radio frequency (RF) subsystems in the same cabinet. The RF subsystems share the same antenna pointing system. The selected frequency bands are the water vapour absorption band (22–30 GHz) and the oxygen absorption band (50–60 GHz). The radiometer is controlled by radiometrics proprietary software and pre-installed control computer. The control computer is connected directly to the radiometer via supplied RS-422 cable. The operating code provides a single use graphical interface that allows the selection of user-defined observation procedures and automated calibration procedure. Real-time observations and calibration data are displayed in graphical format. Now, depending upon the choice of operating codes, it begins logging data to level '0' file (raw sensor data in volts), level '1' file (brightness temperature) and others along with calibration files. The radiometer antenna has its beam with and side lobes 4.9–6.3°; −24 dB (for 22–30 GHz) and 2.4–2.5°; −27 dB (for 50–60 GHz). It has the integration time 0.01–2.5 s and pre-detection channel bandwidth 300 MHz, and depending on the integration time, it possesses the resolution of 0.1–1.0 K. Here, in our study, we have chosen the resolution as 1.0 K.

The laser precipitation monitor of make Thies Clima is used to measure the rainfall intensity even though although it has the capability to measure particle sizes down to 0.16 mm diameter. The instrument has the following characteristics.

The optical laser operates at a wavelength of 785 nm with a maximum power of 0.5 nW. Measuring area is 46 cm^2. The minimum intensity that can be registered by the instrument is 0.0005 mm/h which corresponds to a drizzle, while maximum intensity measurable is 250 mm/h. The integration time for the device is 10 s.

The two instruments mentioned above are used to collect the data on which the estimation techniques are applied. Measurements of attenuation corresponding to rain rate are taken for the frequencies 22.234, 22.5, 23.034, 23.834, 25, 26.234, 28 and 30 GHz. Approximately, 7500 data points are obtained for each of the above-mentioned frequencies, for both attenuation as well as rain rate. Now, estimation models is proposed to estimate rain attenuation from rain rate.

4 Proposed Models and Results

The attenuation and rain rate data obtained through measurement are initially used to propose a power law model for estimation of attenuation from rain rate. The nature of the proposed model is observable in Eq. (1). The rain rate is represented as r, and the corresponding rain attenuation is represented as A.

$$A = X * r^Y \tag{1}$$

The values of X and Y for different frequencies obtained through curve fitting for minimum mean square error (MMSE) fit considering the power law model are shown in Table 1.

The corresponding values of mean error and root mean square error (RMSE) obtained through comparison with actual readings at different frequencies using the power law model are shown in Table 2.

The variation of mean error and RMSE over the given set of frequencies is shown in Fig. 1.

To better the estimation achieved by this model, a machine learning-based adaptive spline model is proposed, which calculates estimates by splitting up the datasets into subsets of 1500 points each and running a linear regression spline estimation on the subsets.

The spline model is piecewise linear in nature, and hence, the equations are constructed using constants P, which is the slope of the equation, and Q, which is the intercept constant, as shown in Eq. (2).

$$A = P * r + Q \tag{2}$$

Table 1 Values of X and Y parameters at different frequencies for power law model

Frequency (GHz)	X	Y
22.234	2.5259	0.5345
22.5	2.3576	0.561
23.034	2.9708	0.4939
23.834	3.6545	0.4269
25	3.2588	0.4757
26.234	2.84	0.5243
28	3.69	0.45
30	4.31	0.4171

Table 2 Mean error and RMSE at different frequencies for power law model

Frequency (GHz)	Mean error	RMSE
22.234	0.25	1.85
22.5	0.38	1.88
23.034	−0.11	1.91
23.834	−0.79	1.91
25	−0.8	1.94
26.234	−0.67	1.93
28	−1.29	1.98
30	−1.64	2.07

The sets of mean error values and RMSEs for all frequencies obtained using the linear spline regression model are shown in Table 3 (Fig. 2).

The RMSE is a better measure of accuracy compared to mean error, and therefore, the RMSEs for both techniques are compared to determine the relative accuracy of the two models. The comparison is graphically represented in Fig. 3.

The estimation values obtained by using the linear spline model are seen to be much more accurate compared to values obtained using the power law model. This clearly shows the advantage of using linear spline for estimation of rain attenuation from rain rate.

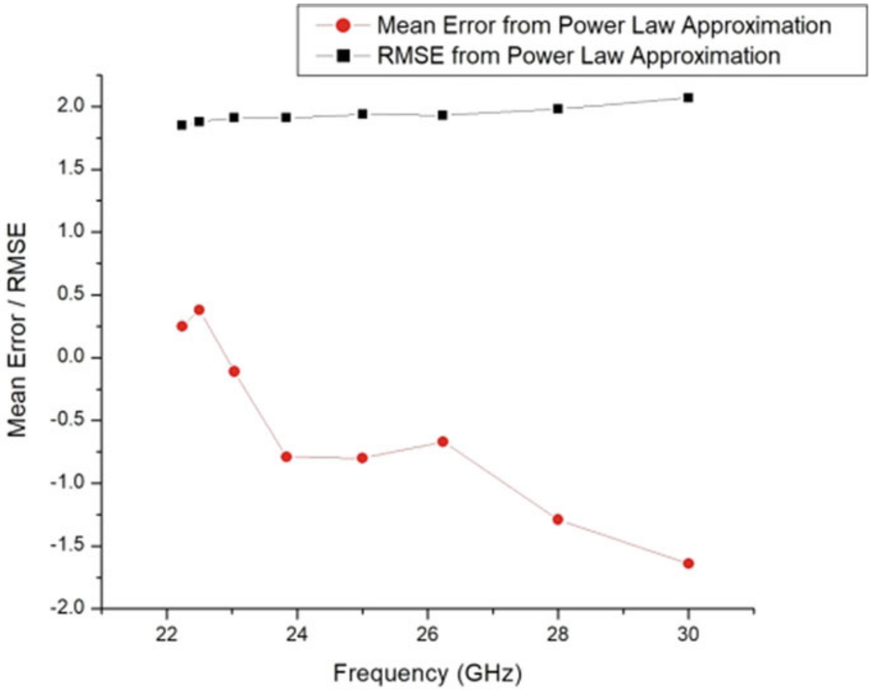

Fig. 1 Mean error and RMSE from power law estimation model

Table 3 Mean error and RMSE at different frequencies for linear spline model

Frequency (GHz)	Mean error	RMSE
22.234	−0.15	1.09
22.5	0	1.04
23.034	0	1.03
23.834	0	1.06
25	0	1.12
26.234	0	1.18
28	0	1.25
30	0	1.36

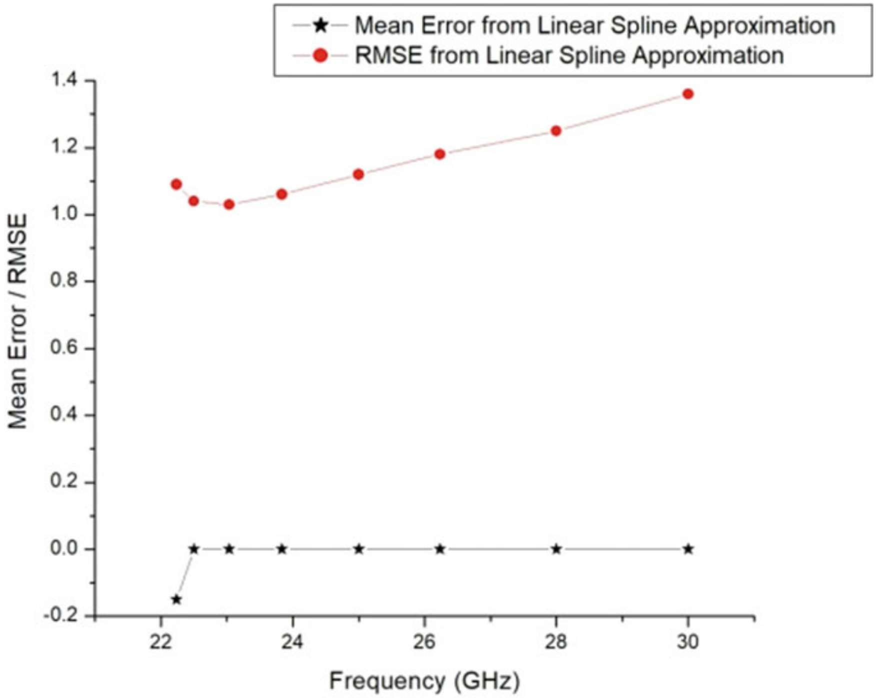

Fig. 2 Mean error and RMSE from linear spline estimation model

5 Conclusion

The machine learning technique used in the current paper has better accuracy compared to the empirical power law model proposed earlier. However, the linear spline estimation used in this paper can be further improved by nonlinear equations for more accurate prediction of nonlinear data points which otherwise may be regarded to be outliers by the linear spline estimation model. Also, classification of data into subsets may be done using other machine learning algorithms such as decision trees or support vector machine (SVM) models. Thus, the authors would endeavour to investigate combinations of machine learning models to improve accuracy. Another avenue of research would be estimation based on neural networks.

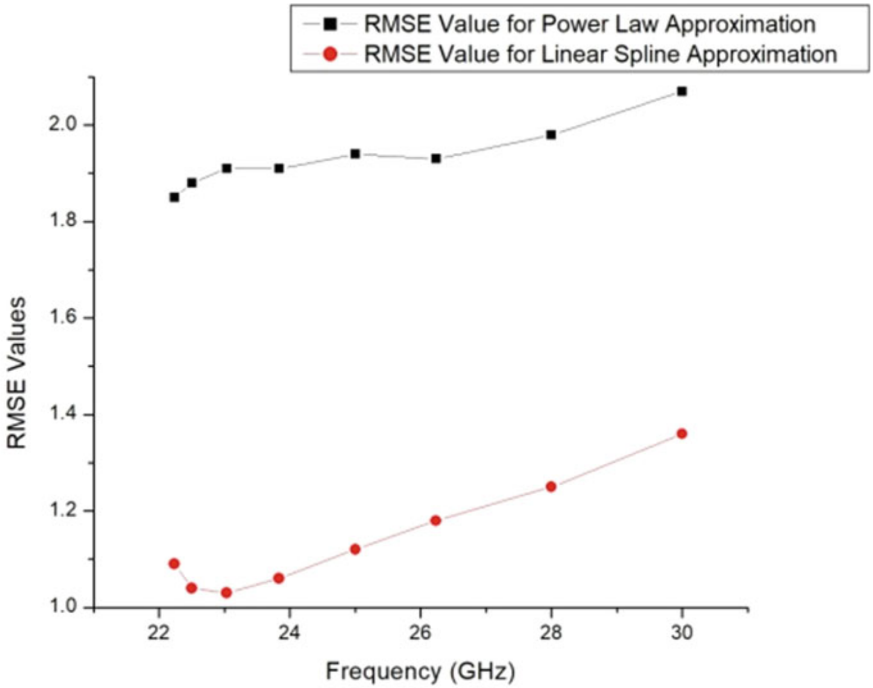

Fig. 3 Comparison of RMSE values obtained by power law and linear spline estimation models

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References

1. Verma, A.K., Jha, K.K.: Rain drop size distribution model for Indian climate. Indian J. Radio Space Phys. **25**, 15–21 (1996)
2. Matricciani, E.: Service oriented statistics of interruption time due to rain fall in earth space communication systems. IEEE Trans. Antennas Propag. **52**(8), 2083–2090 (2004)
3. Kumar, V., Ramachandran, V.: Rain attenuation measurement at 11.6 GHz in Suva, Fiji. Electron. Lett. **40**(2), 1429–1431 (2004)
4. Singh, M.S.J., Hassan, S.I.S., Ain, M.F., Igarashi, K., Tanaka, K., Iida, M.: Rain attenuation model for South East Asia countries. IET Electron. Lett. **43**(2), 75–77 (2007)
5. Mandeep, J.S., Allnutt, J.E.: Rain attenuation predictions at ku-band in South East Asia countries. Prog. Electromagn. Res. **76**, 65–74 (2007)
6. Ramchandran, V., Kumar, V.: Modified rain attenuation model for tropical regions for ku-band signals. Int. J. Satell. Commun. Netw. **25**, 53–67 (2007)
7. Allnutt, J.E.: Slant path attenuation and space diversity results using 11.6 GHz radiometer. Proc. IEE **123**, 1197–1200 (1976)

8. Shayea, I., Rahman, T.A., Azmi, M.H., Islam, M.R.: Real Measurement study for rain rate and rain attenuation conducted over 26 GHz microwave 5G link system in Malaysia. IEEE Access **6**, 19044–19064 (2018)
9. Regonesi, E., Luini, L., Riva, C.: Limitations of the ITU-R P.838-3 model for rain specific attenuation. In: 2019 13th European Conference on Antennas and Propagation (EuCAP), Krakow, Poland, pp. 1–4 (2019)
10. Verma, A.K., Nandan, D.R., Verma, M.A.: Rain drop size distribution and variability of specific rain attenuation for Indian climate. In: 2019 URSI Asia-Pacific Radio Science Conference (AP-RASC), New Delhi, India, pp. 1–4 (2019)
11. Brost, G., Magde, K.: On the processing of loss-of-lock attenuation and rain rate statistics. In: 2019 13th European Conference on Antennas and Propagation (EuCAP), Krakow, Poland, pp. 1–3 (2019)
12. Ahuna, M.N., Afullo, T.J., Alonge, A.A.: Rain attenuation prediction using artificial neural network for dynamic rain fade mitigation. SAIEE Afr. Res. J. **110**(1), 11–18 (2019)
13. Yang, H., He, C., Song, W., Zhu, H.: Using artificial neural network approach to predict rain attenuation on earth-space path. In: IEEE Antennas and Propagation Society International Symposium. Transmitting Waves of Progress to the Next Millennium. 2000 Digest. Held in conjunction with: USNC/URSI National Radio Science Meeting (C), Salt Lake City, UT, vol. 2, pp. 1058–1061 (2000)
14. Sujimol, M.R., Acharya, R., Shahana, K.: Prediction and estimation of rain attenuation of Ka-band signals. In: 2019 URSI Asia-Pacific Radio Science Conference (AP-RASC), New Delhi, India, p. 1 (2019)