

Review

Learning-Assisted Rain Attenuation Prediction Models

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Received: 28 July 2020; Accepted: 27 August 2020; Published: 31 August 2020



Abstract: Rain attenuation becomes significant to degrade the earth-space or terrestrial radio link's signal-to-noise ratio (SNR). So, to maintain the desired SNR level, with the help of fade mitigation techniques (FMTs), it needs to control transmitted signals power considering the expected rainfall. However, since the rain event is a random phenomenon, the rain attenuation that may be experienced by a specific link is difficult to estimate. Many empirical, physical, and compound nature-based models exist in the literature to predict the expected rain attenuation. Furthermore, many optimizations and decision-making functions have become simpler since the development of the learning-assisted (LA) technique. In this work, the LA rain attenuation (LARA) model was classified based on input parameters. Besides, for comparative analysis, each of the supported frequency components of LARA models were tabulated, and an accurate contribution of each model was identified. In contrast to all the currently available LARA models, the accuracy and correlation of input-output parameters are presented. Additionally, it summarizes and discusses open research issues and challenges.

Keywords: rain attenuation; artificial neural network; back-propagation algorithm; machine learning algorithm

1. Introduction

A recent analysis has shown that approximately 50 billion devices will need an Internet connection by 2020; most of them will be wirelessly connected [1]. Rapidly emerging wireless networking systems are beginning to use millimeter-wave frequency bands (30–300 GHz) to transmit data at a growing pace due to the demands of mobile data network service providers.

The rain has a substantial effect on electromagnetic wave propagation. This effect influenced researchers by controlling transmitted power to the counteraction of rain influence on the radio waves. Thus, several experiments on the approximation of rain attenuation techniques have been carried out worldwide. The rain attenuation research is used to study and predict attenuation over a wide variety of frequency bands, especially for bands above 10 GHz [2], in various geographical areas and to identify a suitable model that can estimate attenuation. Identifying the features of a rain attenuation model is one of the most critical activities for the creation of a model. Several variables can affect rain attenuation, such as the transmitter's distance from the receiver, frequency, rainfall intensity, temperature of precipitation, humidity, density, wind speed, and wind direction. However, among the parameters, rain rate and path length are the most important factors. As a result, most rain attenuation models evaluate the relationship between rain rate and path length parameters to rain attenuation.

In order to plan the channel capacity, manage the connection quality, and network design, reliable rain attenuation in a specific radio link is necessary. Often, if other structures of a communication

system operate properly, accessing the possibility of terrestrial or inclined links can be improved with an efficient rain attenuation model. It is also possible to avoid overestimating the transmission system's necessary power by the estimation through the rain attenuation model.

Besides, it is important to meet the spectrum management regulatory organization specification in each frequency range to comply with the permissible requirements for power transmission. In the case of these requirements not being met, the transmitted signal power can interfere with another neighboring frequency band. This intrusion can cause disruptions to neighboring telecommunications equipment.

To the best of our knowledge, in the literature, there exists no survey paper on the learning-assisted rain attenuation model, and this paper presents a comparative analysis of all the available learning-assisted rain attenuation models, such as a classification based on the number of input features, earth-space or terrestrial application cases, advantages, disadvantages, and probable future development. Consequently, the main objective of this paper was to provide the reader with a survey on the existing LARA model, to show the available model's possible future improvement scope/scopes, and to focus on the future direction for improving the LARA model.

1.1. Contributions of This Paper

In this article, we extensively investigate all the published works to the best of our knowledge of rain attenuation based on either the artificial neural network (ANN) or machine learning (ML) techniques. We qualitatively compared the accuracy of the LARA models. The major contributions of this article are:

- The importance of switching from the traditional frequency to a higher frequency spectrum is previewed. Additionally, the reasoning is presented regarding why it needs to regulate the transmitting power at the end of the transmitter in an optimal manner.
- The LARA model's wide range of input features and up-to-date model's learning algorithms are focused on.
- We classified the LARA models based on the number of input features and model structure. Besides, a general scenario of the LARA models, including all the probable input features, is presented.
- A comprehensive picture of all the LARA models is presented. In contrast, the different properties of the models are tabulated: The model's link supports, experimental dataset, supporting frequency bands, model-specific input, optimization techniques used, and performance assessment criteria.
- Finally, open research topics are summarized.

1.2. Outline of the Paper

In Section 2, the rain attenuation factors/features and various used ANN/ML algorithms are illustrated. The remainder of this article is organized as follows: Section 3 presents a description of the taxonomy of the existing rain attenuation model and inputs relevant to the rain attenuation model. Section 4 explores and addresses all available LARA models thoroughly. All the LARA models are compared in terms of their qualitative and quantitative characteristics in Section 5. Section 6 outlines and addresses a wide variety of study issues and challenges. In Section 7, this paper is completed with a conclusion. Figure 1 illustrates the organizational structure of this paper.

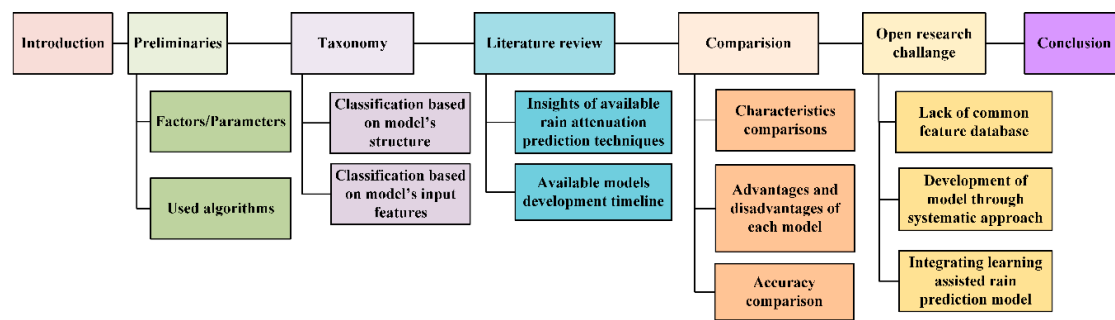


Figure 1. The visual orientation of the paper.

2. Preliminaries

It is reported that the ANN/ML-based rain attenuation model can adopt many parameters compared to the physical or empirical-based models. In this section, a discussion regarding several parameters of LARA models and the algorithms used in these models is provided.

2.1. The Factor of LARA Models

The rationale-cause-based analysis must first be sought in order to develop a good rain attenuation model. In other words, it means finding the factors that affect the rain attenuation. Although the rainfall rate is the most important factor determining attenuation, other factors also possess significance as per several studies. A brief review is presented here regarding more rain attenuation factors.

Lina Zhao et al. [3] listed 10 factors that could affect rain attenuation in the radio link at the frequency component above 10 GHz. The factors include temperature, path length, frequency, precipitation rate, wetness, wind speed, direction, and visibility of the wind. Alencar et al. [4] considered the polarization angle, frequency, station height, height precipitation rate (time percentage), elevation angle, and latitude can affect the attenuation of rainfall.

Thiennviboon et al. [5] considered the precipitation intensity, frequency, latitude, the angle of elevation, and azimuth as attenuation factors for the earth–space link. Mpoporo et al. [6] consider the precipitation rate, azimuth, elevation angle, precipitation height, the percentage of time exceedance, and frequency as a slant link factor as parameters that impact attenuation. V. Kvicera et al. [7] claimed that the rainfall rate and several parameters can affect the rain attenuation, such as moisture and air pressure, wind direction, and wind speed. S. Livieratos et al. [8] developed a supervised machine learning model to take the frequency, rain rate, polarization, and path length as features from the International Telecommunication Union Radiocommunication Sector (ITU-R) database.

Apart from the link length and precipitation rate, most factors may have less influence on rain attenuation, but in order to achieve the highest level of predictive accuracy, it may be necessary to consider such loosely affecting factors in the model. Figure 2 presents a general illustration of the LARA model's input and output parameters. From now and onwards, we will use parameters or features or factors as of equivalent meaning.

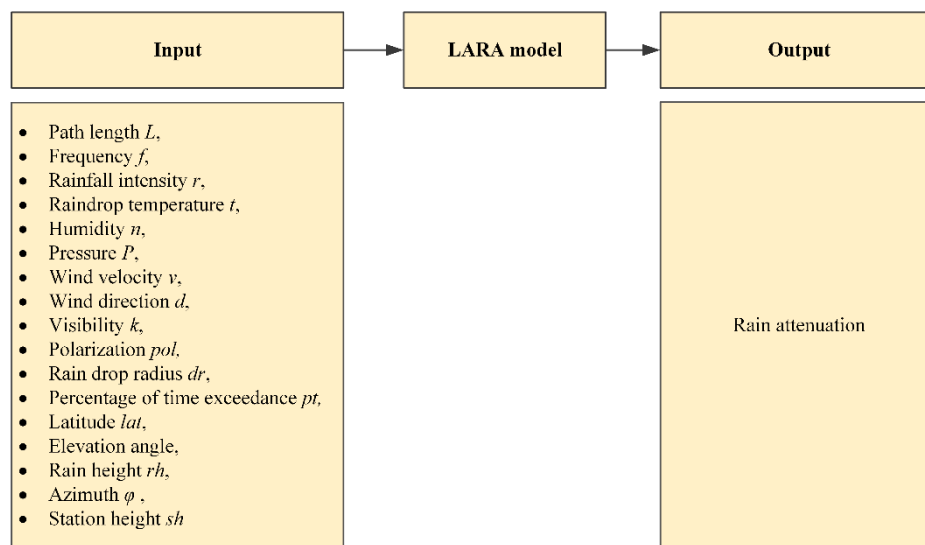


Figure 2. A general illustration of the LARA model's input and output parameters.

2.2. Algorithms Used in LARA Models

Several types of learning-aided algorithms are used to estimate rain attenuation via the LARA models. Mostly, the algorithms used here are a modified version of the back-propagation algorithm and a basic structure of an artificial neural network. Table 1 presents all the learning techniques used for attenuation prediction to date as per the best of our knowledge in major scientific publication database records accessed till July 2020.

2.3. Critical Challenges of LARA Models

The critical challenge of predicting the rain attenuation model compared to the other time-varying model is that there are at least reported 17 input features (Figure 2) that can influence rain attenuation. Although few of these features are a fixed quantity in a particular infrastructure setup, such as station height, azimuth, latitude, polarization, or elevation angle, many of the features have statistical variant behavior, such as rainfall intensity, wind velocity, pressure, raindrop temperature, and raindrop size. Many of these features change over time to time, which may be called statistical variations. The adjustment of these statistical variations may lead to undesirable nonlinear properties in univariate time series. Many of the statistical variation components and nonvariational components are not independent, and thus not separable [9].

Table 1. Learning algorithms used in currently published LARA model's rain attenuation model.

Ref.	Learning Models	Model Structure
[4]	Single-layer feed-forward back-propagation (SL FFBP) model	Back-propagation single layer neural model with a single hidden layer.
[6]	Feedforward back-propagation neural network (FFBNN)	Feedforward back-propagation neural network
[8]	Supervised machine learning (SML)	SVM and SML-based regression algorithm that uses Gaussian process-compatible kernel functions.
[10]	Artificial neural network (ANN) and k-nearest neighbor (kNN)	kNN and ANN (recurrent neural network)
[11]	Back-propagation neural network (BPNN)	BPNN with a sigmoid input function
[12]	Feed-forward multilayer perceptron (FFMLP) in addition to supervised learning (SL)	The network is the multilayer feed-forward (MFF) network; Input section: Bayesian regularization adaptive training algorithm; Activation function: Tangent sigmoid transfer functions (hidden layer) and pure linear transfer function (output layer).
[13]	Least squares-support vector machine (LS-SVM) and BPNN	BPNN: with M layers and N number of nodes
[5]	Single-layer artificial neural network (SL ANN)	LS-SVM: Using LS-SVM to develop a function that can predict attenuation with an unseen rain rate. SL ANN: It is a single hidden layer network.
[14]	In situ learning algorithm (ILA) and adaptive artificial neural network (AANN)	Activation function: hyperbolic-tangent activation function (hidden layer with 5–9 nodes), and linear activation function (output node)
[15]	Regression analysis (RA)*	Regression analysis

* This technique determines specific attenuation coefficient (k and α) rather than predicting the attenuation; consequently, we have limited its use in the later section.

3. Taxonomy

The LARA models are somehow different compared to the traditional rain attenuation models. As the LARA models possess the property like a black-box, and physical significance represents the model input parameters to the output rain attenuation parameters, LARA models can take several input parameters. Whereas, it is complicated to handle many input parameters by an ordinary algorithm-based rain attenuation model. The LARA model can be classified in different perspectives, such as the model structure and training data set.

Based on the model structure, the existing LARA model can be classified into two broad categories: artificial neural network (ANN) and machine learning approach. The ANN-based models can be further classified into two types: tailored and non-tailored model. The tailored model structure is built on a customization style whereas the non-tailored model is almost the basic structure as per its name in the literature. Figure 3 shows the LARA model's classifications based on the model structure.

Within this work, we would like to define the taxonomy based on the number of parameters used by the model. In this way, we classified the model that it takes; one input parameter is considered as a one-factor model.

Similarly, models that are associated with two factors are associated with a two-factors model, and input parameters having three or more models are grouped in the three-or-more-factors-model category. In this way, the complete taxonomy is presented in Figure 4. A mapping of the input parameters of the LARA models is shown in Table 2.

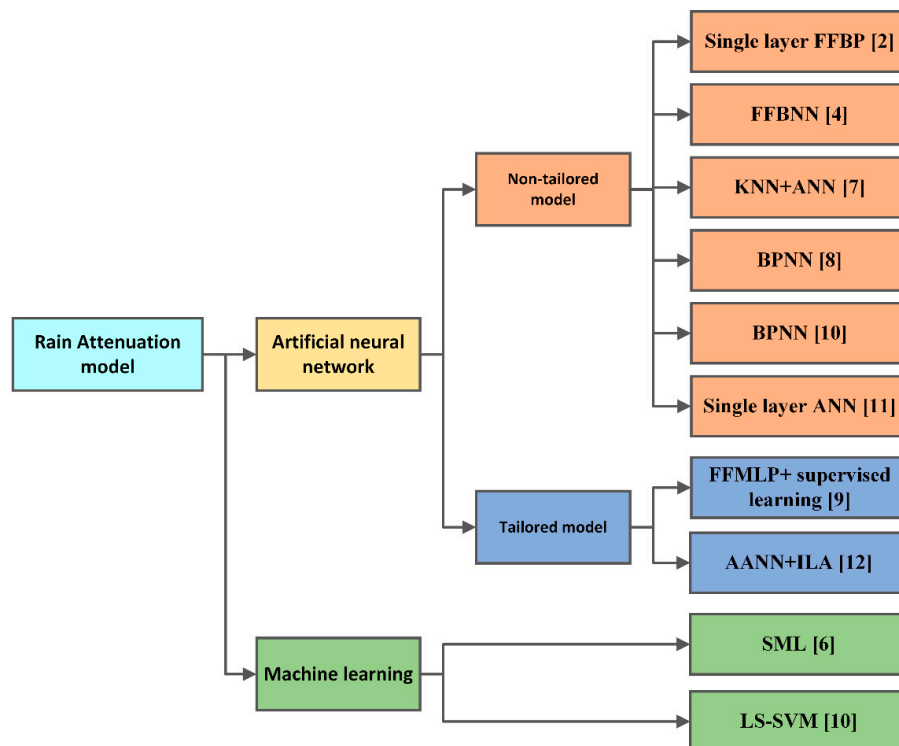


Figure 3. LARA model's taxonomy based on the model structure or formation.

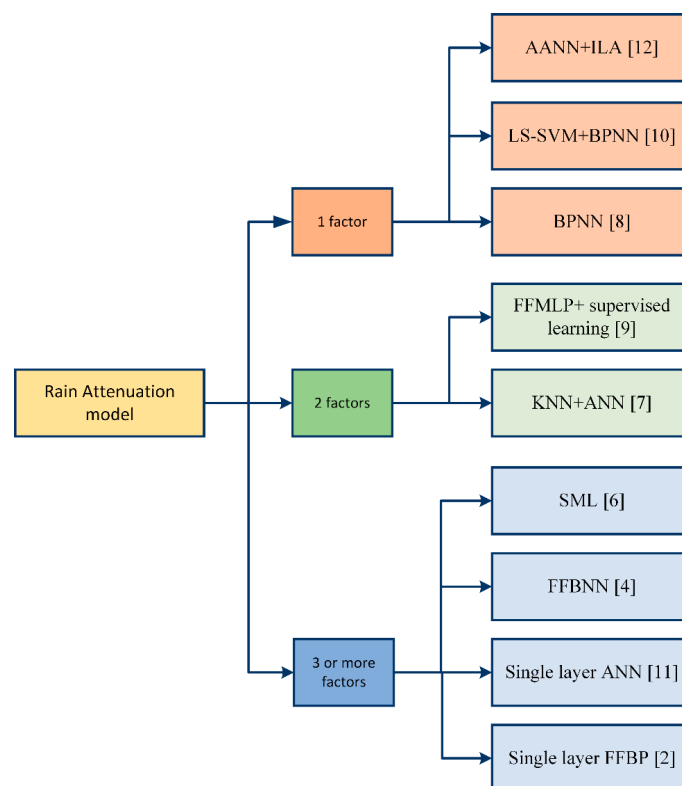


Figure 4. LARA model's taxonomy based on the number of input parameters.

Table 2. The LARA model's input parameters.

	SL FFBP	kNN, ANN	BPNN	FFMLP+SL	FFBNN	LS-SVM+BPNN	SML	SL ANN	AANN+ILA	RA
Station height	√									
Latitude	√							√		
Frequency	√	√		√	√		√	√		
Rain rate	√	√	√		√	√	√	√		
Polarization	√						√			√
Path length							√	√		√
Raindrop radius				√				√		
Elevation angle					√					
Rain height					√					
Percentage of time exceedance					√					
Azimuth					√			√		
Attenuation									√	

√ = The factor belongs to the model.

4. Insights of LARA Models

The number of available LARA models is limited. In this section, the summary, advantages, disadvantages, and the probable future development of each LARA model are presented.

4.1. LARA Model with One Factor

Bijoy Roy et al. [14] used three sites' attenuation data about the 11 GHz frequency to predict the short-term rain attenuation prediction for the standard fade mitigation technique (FMT) application. The technique is composed of AANN that enables predicting short-term rain attenuation while the ILA technique helps in case any rain event behavior is non-stationary (Figure 5). They performed calculated attenuation based on an ideal clear sky-based threshold value to mark the attenuation.

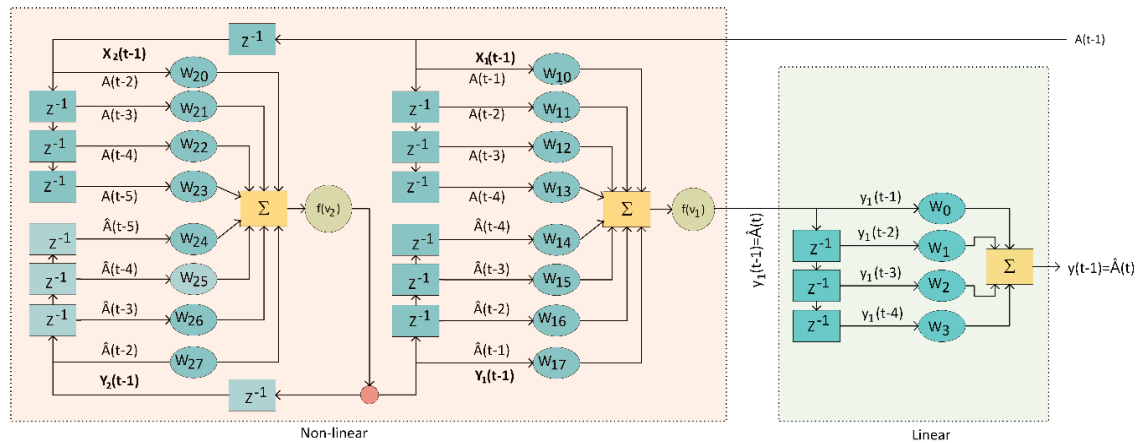


Figure 5. Adaptive Artificial neural network (AANN) to predict short-term rain attenuation.

They observed that at a low-frequency component (near 10 GHz and below), spectral density variations is low, while at higher frequency components, spectral density variations are comparatively higher. Using a window function, they eliminated the fluctuations encountered by higher frequency elements. Additionally, a linear curve is fitted using the least-square fit methodology for all samples within this window range of 10 min length. The weights of non-linear portions are modified by $\Delta w_k(\tau)$, where τ is the sample time. The weights of a non-linear portion of the error at the end of the non-linear portion is minimized through optimization at every sample time at τ :

$$\Delta w_1(t) = 2\lambda^0 \mu e_1(t) f_1' I_1(t-1) \quad (1)$$

$$\Delta w_2(t) = 2\lambda^1 \mu e_2(t) f_2' I_2(t-1) + 2\lambda^0 \mu e_1(t) f_1' f_2' I_2(t-1) \quad (2)$$

$$w_k(t) = w_k(t-1) + \Delta w_k(t) \quad (3)$$

where λ is a forgetting factor ($0 < \lambda < 1$), μ is the learning factor, f_k' is the derivative of the activation function of the k module, and e_1, e_2 are errors.

The error next to the linear block is minimized through modifying the weights of the least mean square technique. If there is a change during a sample time, the new weight will be:

$$w(t) = w(t-1) + \Delta w(t) \quad (4)$$

Advantages: The technique can predict attenuation for in situ application at about 11 GHz frequency components effectively. The model can be applied concerning the short-term prediction of rain attenuation for FMT operation.

Disadvantages: The technique cannot determine or predict attenuation for scintillation that experiences fast fluctuations.

Future improvement: To deploy measures to predict attenuation at higher frequency components. They had added a variable margin to the expected value in an efficient fashion to increase the excess over bound, resulting in recourse drainage.

Lina Zhao et al. [13] suggested two methods: the least square-support vector machine (LS-SVM) and the synaptic back-propagation (BP) technique. All strategies can forecast attenuation by taking the strength of the rainfall as the reference.

For the BP-based model, they used 78 samples of the rainfall date to feed in a BP network that consisted of unregulated synaptic weights. However, after feeding a sample to the network, the network can calculate the attenuation based on the current synaptic weight. At this point, the mean-square error is measured. This error is propagated in the backward direction to measure and change the model's synaptic weights, recognizing that there might be a threshold error value. They repeated this process for the rest of the 77 samples as well. Based on this experiment, they chose a BP network that consists of single input and output node and a single hidden layer that consists of 13 nodes and optimized synaptic weights.

For the LS-SVM case, they used the training data set $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \in R_n \times A_n$, where R_n is the rainfall intensity and A_n is the rain attenuation. From higher-dimension feature space, optimal linear regression function can be obtained.

Advantages: The method can accurately forecast attenuation for 60 GHz, and the experimental findings demonstrate that both models outperform the ITU-R model.

Disadvantages: It is not mentioned whether the training data is from the terrestrial or the earth-space link.

Future improvement: As a result, the LS-SVM can forecast rain attenuation with improved efficiency, compromising accuracy. However, the accuracy needs to be increased.

MN Ahuna et al. [11] developed a rainfall forecast model based on a back-propagation neural network (BPNN) with four years of data collected. The model's predicted results matched with two years of real rain rate from 2017 to 2018. The BPNN network consists of input, hidden, and output layers. The synaptic weights are updated by the backpropagation with the condition that:

$$\frac{dE}{dO_a} = -(O_t - O_a), \quad (5)$$

where O_t is the desired output (target), O_a is the actual output, and E is the error. The minimum error results in:

$$\Delta w_i = \eta \left. \frac{dE}{dO_i} \right|_{i=1,2,3,\dots,l}, \quad (6)$$

where Δw_i is the weight change on the i th input, η is the learning rate, O_i is the output contributed by the i th input, and i is the input.

This results in a BPNN network that consists of a single input, a single output layer, three hidden layers, and consists of three nodes. Further, they calculated the directional synaptic weight matrices in the forward and backward direction as well as synaptic weights.

Advantages: As per the validation result, the model can successfully predict the attenuation.

Disadvantages: The model needs low sample timings of 1 min or less. Further, they created five attenuation classes, and they did not justify these five attenuation class boundaries' marking.

Future improvement: Find the BPNN models' structure and weight matrices for relatively short sample timings of about 10 s.

4.2. LARA Model with Two Factors

Amarjit et al. [12] established an ANN model that uses horizontal or vertical polarized frequency components of the input and extinction cross-section as output, varying from 1 to 100 GHz and raindrop diameter (Figure 6). They used the Bayesian regularization adaptive training algorithm to train the neural network. They used prespecified mean square error (MSE) as the threshold level to determine

the optimized extinction cross-section in addition to the correlation coefficient between the actual and predicted values (R^2) for India and Singapore experimental dataset datasets.

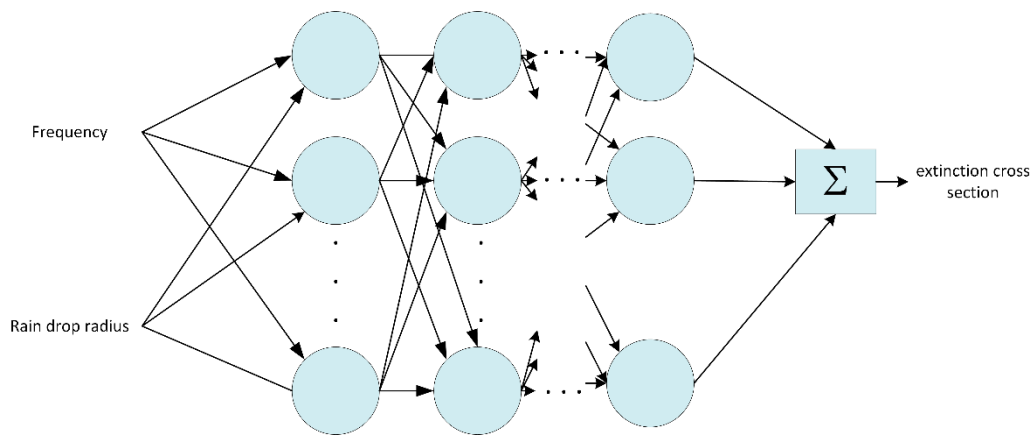


Figure 6. Adaptive ANN to predict short-term rain attenuation.

Advantages: The technique has a wide range of frequency supporting facilities (1–100 GHz). Maybe this technique can be applied easily with the frequency scaling in the satellite downlink channel as the technique is already using the drop size distribution (DSD)-based raindrop distribution.

Disadvantages: It is not mentioned whether the training data is from the terrestrial or earth–space link.

Future improvement: As the technique already supports the vertical and horizontal polarization, it needs to add circular polarization.

Tansheng Li et al. [10] proposed short-term rain attenuation for ground wireless communications using k-nearest neighbor (kNN) with an artificial neural network (ANN). The time-series of relation attenuation measured from a collection of high-precision radar precipitation maps was used as training data.

Advantages: As the specific rain attenuation rate is calculated from the radar-originated rain map, the rain information is more a granular type, e.g., comparatively, almost real rain distribution is attainable. This result leads to the training of the ANN network being built with comparatively accurate data.

Disadvantages: The technique used here requires a 5 min rain rate. In the case of a sparse rain distribution in a map, then the kNN and ANN-based techniques may give an erroneous result.

Future improvement: Although the radar map-based rain attenuation extracting technique may be helpful without deploying the rain gauge data collected, another procedure may have some truncation error. The real wireless device that can be deployed to collect the attenuation data might give a high-precision reduction of rain attenuation.

Application area: The model is useful for short-term rainfall model application, e.g., FMT operation

4.3. LARA Model with Three or More Factors

S. Livieratos et al. [8] developed this model based on the SML algorithm applied to the ITU database. If the available data set is classified as discrete data, SML is used, whereas, for continuous data, the regression SML model is used. The theory of SML is combined with Gaussian processes (GPs) for regression, called GPR, to create a new approach for forecasting rain attenuation. This model was validated using experimental data from the ITU-R database for the line-of-sight (LOS) terrestrial link. To find out the rain attenuation in a specific geographical area, climatic zones or frequency bands need to train the algorithm to calculate the different interdependence of various parameters. The model is then able to predict the attenuation in that area of interest. Hence, this model, like other machine

learning models, cannot be applied directly in a climatic area, except before training with the local data set.

Advantages: It is the first machine learning-based model without geographical boundness.

Disadvantages: The tropical behaviors of attenuation have not been tested yet using this model.

Future improvement: For the rare climatic condition, it needs to train the algorithm with the specific dataset.

Application Area: To predict rain attenuation on a terrestrial link with the millimeter frequency component.

LJ Mpoporo et al. [6] introduced the adoption of artificial neural networks (ANNs) as a strategy for calculating rain-induced attenuation along with higher frequency satellite connections in South Africa. The proposed ANN model suggested an improved estimation efficiency in terms of the root mean square error and correlation coefficient. The model's five factors are considered as the input (rain intensity, the angle of elevation, the percentage of the time, frequency, a latitude), and the output is the rain attenuation. The weights are modified using the gradient descent method to keep the error in the output to a minimum.

Advantages: The model considers five input parameters set to determine the rain attenuation.

Disadvantages: To use this model, it needs a 5 min rainfall rate. Currently, numerous rain attenuation databases with a 1 min rain rate are normally available.

Future improvement: Develop the same model for a 1 min rain rate.

Application area: The model can predict rain attenuation of the 12 GHz frequency component on the earth-space link.

P Thiennviboon et al. [5] proposed a model ANN network to predict the earth-space rain attenuation model. In the model, they used six parameters as input parameters of the ANN network, and attenuation is the output. Throughout this paper, the authors emphasized the significance of a big database of differences throughout various parameters. They consider an ANN model consists of six input nodes, a hidden layer (an unknown number of nodes), and the output layer.

Advantages: A very simple ANN network can outperform the existing model.

Disadvantages: Needs a huge task to prepare a database compatible with the model.

Future improvement: The model's consistency of feature ideas can be tested for other factors to examine any consistency anomalies.

Application area: The model can be used to predict rain attenuation prediction in the earth-space link.

GA Alencar et al. [4] suggested a rain attenuation prediction model based on FFBP for earth-space links. Further, they used the anomaly of feeding features into the ANN network if low statistical data exists, and also proposed a mechanism to process low statistical data for feeding to the ANN network. Low statistical data is processed through the equation:

$$J = \sum \|\bar{x}_j - \bar{c}_i\|^2, \quad (7)$$

where \bar{x}_j is the j th input-output pair; \bar{c}_i is the center of the i th class mean value of the vector \bar{x}_j belongs to the class, and the sum of the distance between each vector \bar{x}_j and the center of the class is minimized.

Advantages: It describes a mechanism to eliminate low statistical data.

Disadvantages: The structural information regarding the structure of the ANN network is not provided in the article.

Future improvement: Low statistical data idea can be used with a well-designed ANN structure.

Application area: To predict rain attenuation.

In the above section, all the available LARA models were discussed. Figure 7 presents the timeline of the outcome of the LARA model yearly. It is noticeable from the figure that, starting in the year of 2004 with a single publication, there are few year gaps in the year with LARA model publications.

However, in the year 2019, four LARA models were published. This means researchers were becoming interested in developing learning-assisted rain attenuation prediction models.

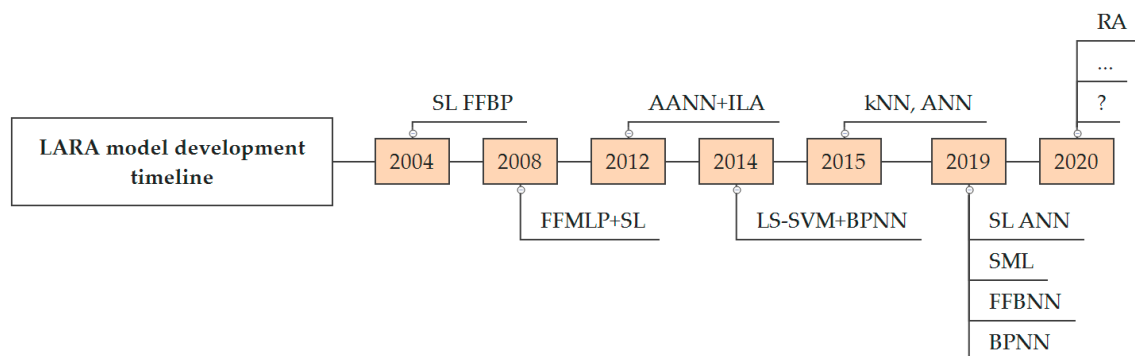


Figure 7. LARA model's development timeline.

5. Comparison of LARA Models of Rain Attenuation

This section compares the performance of current LARA models in terms of factors/parameters/features, satellite or terrestrial connections, supporting polarization, and frequency components (Table 3). All the relevant inputs, optimization, and performance parameters of all available for LARA models are tabulated in Table 4. Figure 8 shows a radar map representing the major features of the available LARA models. As we can see, four LARA models [5,8,13,15] support the polarization while the LARA model [6] includes the maximum number of parameters, which is six. The LARA model [8,12,15] supports the frequency range of 137, 100, and 100 GHz, respectively. Besides, the models [12,13,15] support both the earth–space and terrestrial links. The model-specific contributions, optimization and evaluation criteria, accuracy level, and input-output parameter correlation (R^2) are compared in Tables 4 and 5, respectively. Figure 9 (Root-mean-square error (RMSE) versus model) shows that RA [15] has the least RMSE value following the minimum RMSE models, which are AANN+ILA [14] and SL FFBP [4]. Regarding model FFMLP+SL [12], we cannot get a comparative result, but following the remarks about Relative RMSE (RRMSE) accuracy [16], $RRMSE = 8.5\%$ can be considered as an excellent result, concerning the models' applicability.

Table 3. Few characteristics of the LARA models.

Learning Model	Features and Training Data Set	Sat.	Terr.	Pol.	Dataset	Frequency	Filter?	Data Interval
Single-layer FFBP [4]	rainfall intensity, latitude, elevation angle, polarization, station height, and frequency	$\sqrt{^2}$	\times^3	? ⁴	Own dataset + ITU-R database	?	Y	unavailable
FFBNN [6]	rainfall intensity, the percentage of time exceedance, frequency, elevation angle, rain height, and azimuth	$\sqrt{}$	\times	?	Collected dataset (Beaufort West, Nelspruit, Polokwane, and Pretoria)	12 GHz	N	5 min
SML [8]	distance between transmitter and receiver (0.5 km to 58 km), frequency, rainfall intensity (9 rain rate), and polarization (0° to 90°)	\times	$\sqrt{}$	$\sqrt{}$	ITU-R database	7 to 137 GHz	N	unavailable
kNN, ANN [10]	rainfall intensity, and frequency	\times	$\sqrt{}$?	TMPA-RT ⁵ datasets provided by NASA satellites	32 GHz (experimental)	N	unavailable
BPNN [11]	rainfall intensity	?	\times	?	The University of KwaZulu-Natal, Durban [17,18]	?	N	30 s
FFMLP+ supervised learning [12]	raindrop radius, and frequency	$\sqrt{}$	$\sqrt{}$ [19]	$\sqrt{}$	Database: Singapore and India	1 to 100 GHz	N	X
LS-SVM+BPNN [13]	rainfall intensity	$\sqrt{}$	$\sqrt{}$?	Dataset [7]	Fixed: 60 GHz	N	unavailable
Single-layer ANN [5]	rainfall intensity, frequency, L^1 , latitude, elevation angle, and azimuth	$\sqrt{}$	\times	$\sqrt{}$	YEO [20], DBSG3 [21]	10 GHz to 50 GHz	N	1 min
AANN+ILA [14]	attenuation (recorded)	$\sqrt{}$	\times	?	Collected dataset (INRAPHEL, Kolkata; IIT, Kharagpur; MCF, Hassan)	?	Y	5 s
RA [15]	Rainfall intensity, the distance between transmitter and receiver	$\sqrt{}$	$\sqrt{}$	$\sqrt{^6}$	ITU-R database	~100GHz		

¹ refer to [7] (Table I), ² Supports, ³ Information unavailable, ⁴ unavailable, ⁵ TRMM Multi-satellite Precipitation Analysis (TMPA), near Real-Time (RT), ⁶ inherent with k and α (RA [15] case only).

Table 4. Contributions, optimization, and evaluation criteria of LARA models.

Learning Model	Contribution	Optimization Technique	Optimization	Performance Criteria	Remarks
Single-layer FFBP [4]	To develop a model that can predict attenuation from an unevenly distributed dataset with the aid of divisive hierarchical clustering (DHC) algorithm.	unavailable	unavailable	The cumulative distance from the center of each vector is minimized.	Complete model
FFBNN [6]	This developed model can predict the rain attenuation in South Africa most accurately compared with the ITU-R, SAM model for different percent of time exceedance (1, 0.1, and 0.01).	Gradient descent	$R^2 = 0.99992$ with 0.01 percent of time exceedance	Root mean square error and the correlation error coefficient R^2	Complete model. The result for frequency around 100 GHz has not been justified.
SML [8]	Develop an SML based rain attenuation model (with an estimator) based on the ITU-R model [22]	Apply hyper-parameters as a result of maximization of the marginal likelihood	$R^2 = 0.85$	1. individual conditional expectation visualization ($A_{0.01}$ concerning operational frequency or ITU-R or $R_{0.01}$), 2. Exceeding the chance of rainfall in different parts of the world	This method includes four parameters of rain attenuation and gives attenuation that is almost close to the real measured value.
kNN+ANN [10]	This model uses the rainfall map data along with the KNN and ANN approach. According to their result, when the training dataset is large KNN method becomes more accurate than the ANN method. However, under a certain condition, for example, lower sampling rate shows satisfactory results.	unavailable	Not reported	1. Root mean square error (RMSE): 0.8 (KNN) and 0.5 (ANN) 2. No regression coefficient was reported	Complete model (Developed from rainfall radar map)
BPNN [11]	Develop a BPNN based model that can predict rain rate in a link	Obtained optimized synaptic weights in training period through gradient descent	For regression coefficient $R^2 = 0.91094$ the actual output and predicted output almost agree	Performance is not analytically validated. However, a graph in the paper shows that the predicted rainfall rate almost follows the actual rainfall rates.	Rain rate predicted by the BPNN model and then this rain rate is applied to a hybrid model [23,24]

Table 4. Cont.

Learning Model	Contribution	Optimization Technique	Optimization	Performance Criteria	Remarks
FFMLP+ supervised learning [12]	The model agrees with the experimental attenuation with the rain rate for a rain rate up to 80 mm/h, and after this rain rate, the predicted attenuation is higher compared to the experimental attenuation.	Back-propagation algorithm-based delta rule.	$R^2 = 0.9994$ with error 1.62×10^{-4} for vertical polarization ($R^2 = 0.9943$ with error 4.677×10^{-3} for horizontal polarization)	percentage of relative mean square error	Complete model
LS-SVM+BPNN [13]	BPNN outperforms ITU-R in terms of accuracy and stability. LS-SVM has a better performance compared to ITU-R with neglecting accuracy and stability.	Multilayer-feed forward algorithm-based delta rule is used to optimize the node weights.	BPNN: pre-determined threshold LS-SVM: Python2.7 with $c = 4096$, $g = 1$, $p = 1$	mean absolute error (MAE), maximum error (MAX), and mean square error (MSE)	Complete model
Single-layer ANN [5]	Develop a rain attenuation model composed of six input parameters single layer ANN network to predict the rain attenuation.	Gradient descent method	Not reported	Mean (%), RMS (%), and STD (%) error experimented on the DBSG3 plus tropical database [21]	
AANN+ILA [14]	Develop a rain attenuation prediction technique using a learning algorithm where measured attenuation is used to develop the model.	The LMS algorithm minimizes an instantaneous estimate of the overall cost function and tapped delay filter predicted the local minimization	A more accurate prediction is confirmed by reducing the observation interval.	Relative prediction error can be analyzed to get smoothed attenuation prediction.	Complete model (from attenuation data, not rain data + short term)
RA [15]	Develop and train k and α values prediction for a frequency	unavailable	Not mentioned	Performance not validated	ITU-R companion model

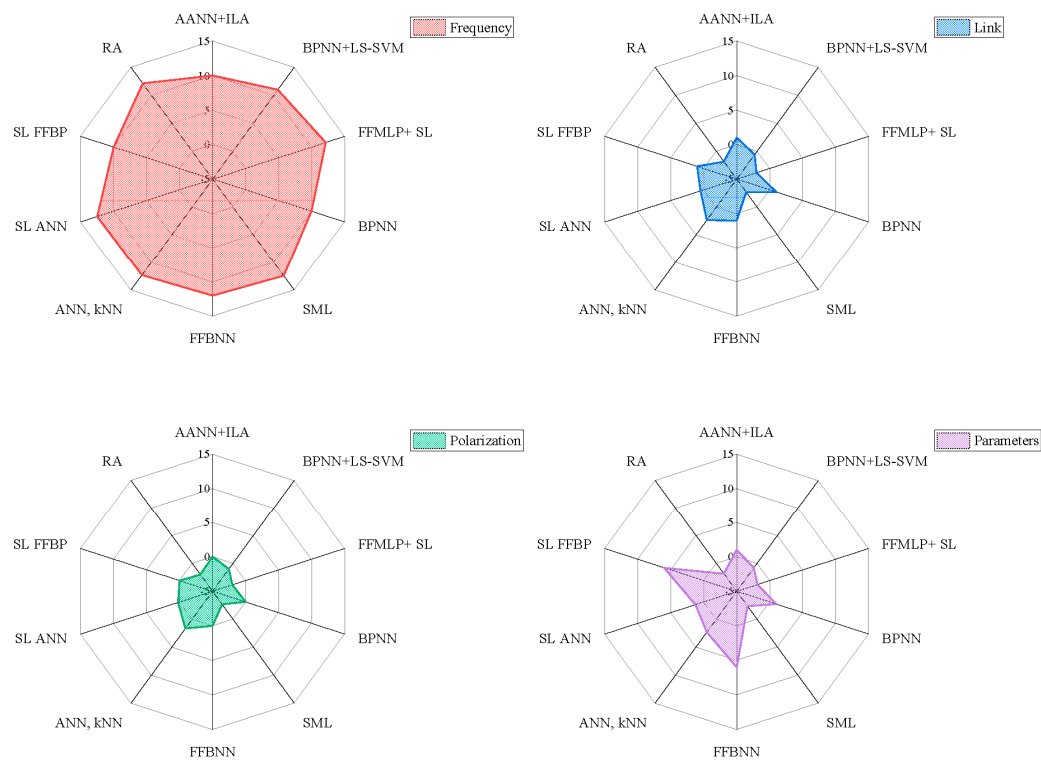


Figure 8. These radar maps show the supported maximum frequency limit, types of supported links (earth-space or terrestrial or both), support for polarization characterizes, and the number of input parameters associated with LARA models. This radar map is visualized with the data from Tables 2 and 3. For better visualization, data range was rescaled from -5 to $+15$.

Table 5. Accuracy and R^2 of the LARA models.

Model	Accuracy	R^2
SL FFBP [4]	RMSE = 0.06 (2000 epoch)	×
FFBNN [6]	RMSE = 0.037749~0.71591	0.97226~1
SML [8]	×	×
kNN+ANN [10]	kNN: RMSE = 0.8 ANN: RMSE = 0.5	×
BPNN [11]	×	×
FFMLP+SL [12]	RRMSE = 8.5%	0.9989
LS-SVM+BPNN [13]	RMSE = 0.4362	×
SL ANN [5]	RMSE = 0.2320~23.20% (YEO) RMSE = 0.2578~25.78% (DBSG3)	×
AANN+ILA [14]	Accuracy = 95% (20 s interval)	×
RA [16]	Accuracy = 97%	×

× = unavailable.

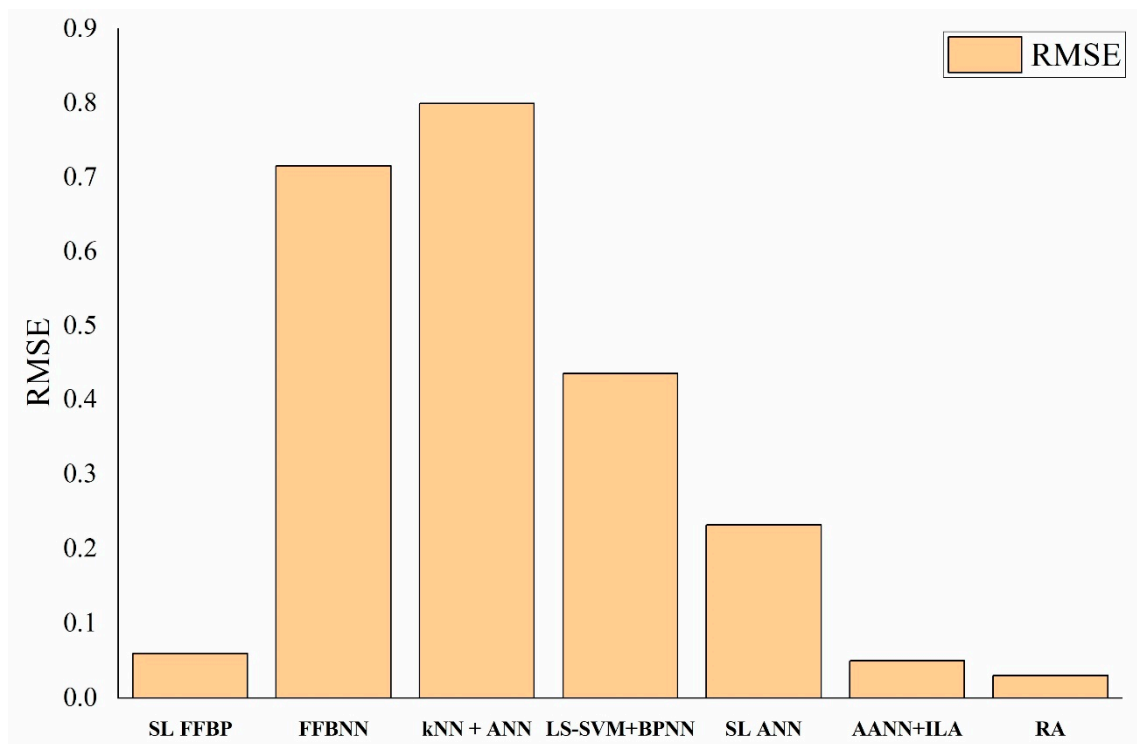


Figure 9. The bar chart shows the root mean square error (RMSE) of few LARA models. For simplicity, the accuracy value of AANN+ILA [12], and RA [13] was considered as the 0.05 and 0.03 RMSE value, respectively. Besides, we could not plot SML [6], and BPNN [8] due to data unavailability, and FFMLP+SL [9] due to data mismatch. Further, if there exists a range of RMSE values (Table 5), we considered the maximum RMSE for such cases.

6. Open Research Issues and Challenges

Significant open research problems, difficulties, and strategies explored in the sense of rain attenuation are covered in this section. Three types of machine learning approaches can aid the LARA model, and these are the machine learning-assisted rain attenuation model, rain type prediction model, and prediction of rainfall from rain attenuated dataset for microwave links. The prediction models of rain attenuation aided by machine learning are still in the process of growth and subject to a comprehensive study. We discussed in Section 2 that there are several possible parameters for the rain attenuation model. However, as mentioned earlier, among these parameters, rainfall and the distance between the transmitter and receiver antenna are very important parameters as most of the models include these factors. Among these two parameters, distance represents comparatively easily collectible information from the link dataset. However, rainfall is a random event that is hard to predict. Fortunately, there are many available techniques to predict rainfall as per weather communities' interests. Besides, accurate rainfall and rain type determination is another fine-estimated data feeding approach that can aid the rain attenuation model.

6.1. Integrating Learning-Based Rainfall Prediction

In [10], a radar-based rainfall map was used to predict rain attenuation using kNN and ANN learning techniques. In [25], it was shown that the radar-originated rain map can preserve the side diversity (distance dependence of rainfall correlation), and transforming this rain map-originated rain rate can help to improve the rain attenuation prediction capability. Inspired by the works [10,25], a question arises whether it is possible to use rainfall prediction data to estimate rain attenuation with a good accuracy level? In fact, among many rainfall prediction techniques recently emerged, the commercial microwave links (CMLs)-based technique, and the learning-based rainfall prediction

technique can be a good candidate to use for rain attenuation estimation. The CML-based machine learning or prediction of rain data through a learning algorithm or radar or satellite-based machine learning model can be used as the aided tool for better rain attenuation prediction. Yen, M.-H. et al. [26] suggested an echo state network (ESN) and deep ESN model where the training dataset was the hourly meteorological data at the Tainan Observatory in southern Taiwan from 2002 to 2014. The model is a good candidate to predict almost a similar region's rainfall rate. However, training with a similar type of dataset, it may be possible to predict the future rainfall rate. The key drawback of the tactic is that the recorded weather training and recorded data on the implementation area should be almost correlated. In fact, many techniques exist in the literature that can predict the rainfall rate. Since 2000, the numerical weather prediction (NWP) technique has gained in popularity to predict rainfall and thus get the attention of weather prediction industries, researchers, as well as other stakeholders. However, due to limited portability, the NWP-based technique may not be a good candidate for use in remote locations. Consequently, learning-assisted rain attenuation prediction will get popularity as it can solve the problems with NWP techniques. In [27–36], the machine learning-based rainfall prediction techniques were presented.

6.2. Lack of Common Database Including Different Parameters

In Figure 2, the input section includes a list of 17 features can influence the degree of rain attenuation. So, to collect all the input features values, an experimental setup is necessary to collect all the feature's datasets. Until now, the ITU has few of these features' dataset, but that does not contain all sets. Consequently, an individual researcher has to collect most of the dataset from the experimental setup. As a result, to do an experiment based on the LARA model, an expensive and time-consuming experimental setup is necessary. Besides, an erroneous individual experimental setup may result in an erroneous dataset that may hamper the purpose of the study. So, to develop a good model and compare it with the existing model, a standard dataset is needed.

6.3. Data Preprocessing

In most cases, for high frequency, the fluctuation in the amplitude of attenuation variation is noisy. For this reason, it needs to use an appropriate filtering technique to remove the noise.

6.4. Non-Linear High Dimensional Space

Even after developing a model for a geographic area, they may need to be adapted to the changes in the feature values for the rain rate, wind, and wind direction. For the real-time FMT applications to adapt such variations, it needs a higher number of neurons in the learning mechanism. However, a higher number of neurons creates huge complexity to the network. Nevertheless, the benefit of such a network is that it can adapt the features statistical variations as well as models' overfitting and underfitting problems. In [5], this overfitting problem is addressed through the expansion mechanism of feature spaces, and in [10], such feature expansion is done with the help of three-feature expansion for better prediction.

6.5. Optimized Rain Attenuation Model

In Section 2, we discussed many probable input features for determining the attenuation using the learning-assisted model. However, in many such models, unimportant features are rejected through feature reduction techniques. Regarding rain attenuation model development, until now, no model has been developed with systematic feature reduction methods. Thus, a systematic approach can be followed to reduce loosely correlated features, and in that way, a model with appropriate features may be developed.

7. Conclusions

Deploying a learning-assisted approach to the rain attenuation model is a new and rapidly increasing research field with a small range of research findings until now. We provided a detailed and comparative analysis of the attenuation of rain for earth–space and terrestrial relations in this paper. The currently available LARA models were classified according to the number of features to the input. The contribution of each published LARA model was addressed precisely, and the learning model optimization techniques were clearly outlined. The accuracy of the LARA models was accessed through a comparative study. This comparative study gives an overview idea about these models. This comparison may help future researchers to establish upcoming models of rain attenuation. Besides, it outlined and discussed critical open science problems and challenges.

Author Contributions: M.A.S. reviewed, analyzed, and summarized the learning-assisted rain attenuation models. D.-Y.C. contributed to research supervision. The paper was drafted by M.A.S. and subsequently revised and approved by D.-Y.C. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by research fund from Chosun University 2020.

Acknowledgments: The authors would like to thank the editor and the anonymous reviewers for their valuable feedback on improving this article's quality.

Conflicts of Interest: The authors declare no conflict of interest.

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