ARTIFICIAL NEURAL NETWORKS AS RAIN ATTENUATION PREDICTORS IN EARTH-SPACE PATHS

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ABSTRACT

The satellite communication services have grown on last years and the radiowave spectrum to support them is saturated. So, it's necessary to search for frequency bands higher than the presently used ones, to allocate new services. But the problem of radiowave degradation by rain is critical for communication links operating above 10 GHz, and a precise knowledge of rain attenuation is important to design reliable satellite communication links, considering that it must operate under all atmospheric conditions. Several phenomenological models have been developed to predict the rain attenuation in earth-space paths, but these models show poor accuracy for higher frequencies. In order to improve the prediction, this paper introduces a new method to evaluate the rain attenuation in satellite communication links using a specially designed neural network. The results show that this new model performs much better than the classical ones.

1. INTRODUCTION

Artificial neural networks are an attempt to simulate, at least partially, the structure and functions of nervous systems of living creatures. In general, an artificial neural network is an information or signal processing system composed by simple processing elements, called artificial neurons, which are interconnected by direct links called synapses. These structures cooperate to perform parallel distributed processing in order to solve a desired computational task. One of the attractive features of neural networks is their capability to adapt themselves to special environmental conditions by changing their connection strengths (synaptic weights) based on an error-correction learning rule. By means of a computational program, it is possible to implement artificial neural networks to solve very complex problems in a wide variety of areas [1].

This paper discusses the specific design and shows the results of a neural network used to predict the rain attenuation in earth-space paths at high frequencies. To the neural network development and analysis we used the data bank from UIT-R (or ITU-R, Radio-communication Sector of International Telecommunication Union) [2], relating frequency, polarization angle, elevation angle, latitude, station height and rain rate for a given time percentage of the average year, to the attenuation that is not exceeded for that time percentage of the average year. For simplicity, from now on we will call those last three variables just *rain rate, attenuation* and *time percentage*. This attenuation is a critical parameter in the design of reliable communications links. At this data bank, several experiments of attenuation in earth-space paths performed around the world can be found and used to test the prediction models. Unfortunately only 80 to 160 complete data cases are available, depending on the time percentage. Moreover, some critical variables, e.g. rain rate and attenuation, are not very precise. But this data bank is the only one available in the word.

The neural network was designed to predict the rain attenuation for time percentages from 0.001 to 0.5% at frequency range from 11 to 20 GHz. The root mean squared (RMS) relative error, E in eq. 1, is the demerit factor proposed by ITU-R to evaluate the performance of a model. To judge the merit of the neural model, a comparative analysis with UIT-R [3], American [4], Japanese [5], Spanish [6] and Brazilian [7] phenomenological prediction models was carried out.

2. THE NEURAL NETWORK

A single intermediate layer feedforward neural network was implemented in a computational program to predict the rain attenuation. Such neural network structure, although simple, is an universal approximator and may be used as a practical way to realize any linear or nonlinear input-output mapping [8].

We decided to use one specific network for each time percentage. The network receives six input signals (frequency, latitude, polarization angle, elevation angle, station height and rain rate), and predicts the attenuation at its output. Some experiments had shown that one linear neuron at the output layer and that 15 neurons with hiperbolic tangent as activation function at the intermediate layer is an adequate choice for our problem. Figure 1 shows the schematic of the applied neural network topology.

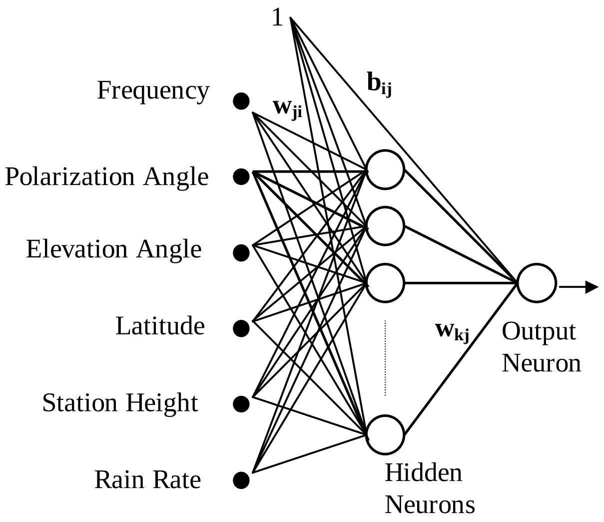

Figure 1: Neural Network Architecture

The neural network undergoes a supervised training that is a modified version of the well known back-propagation algorithm [9]. For the neural model to reach the best performance, the objective function used to train the neural network must minimizes the demerit function proposed by UIT-R, the mean-squared relative error E shown in eq. 1. The function F shown in eq. 2 does the job, and will be used. The essence of back-propagation algorithm is to slightly modify the synaptic weights vector $\vec{w}$ in the direction bur in opposite sense of the gradient of $F(\vec{w})$, in such a way that the discrepancy between the actual output signal and the desired signal is reduced at each step, finishing at a sufficiently small value for most input-output pairs. The input-output pairs are constituted by the six inputs and the desired output, the measured attenuation.

$$E(\vec{w}) = \sqrt{F(\vec{w})} \quad (1)$$

$$F(\vec{w}) = \frac{1}{P}\sum_{p=1}^{P} {e_R}^2(p) = \mu^2 + \sigma^2 \quad (2)$$

where

$$e_R(p) = \frac{A_m(p) - A_e(p,\vec{w})}{A_m(p)} \quad (3)$$

$$\mu = \frac{1}{P}\sum_{p=1}^{P} e_R(p)$$

$$\sigma^2 = \frac{1}{P}\sum_{p=1}^{P}\left[e_R(p) - \mu\right]^2$$

where $\vec{w}$ is the synapses vector, $A_m(p)$ is the measured attenuation and $A_e(p)$ is the attenuation estimated by the model for the input-output pair p. μ is the mean and σ is the standard deviation of $e_R(p)$; P is the total number of available input-output pairs. In the present case usually $\sigma^2 >> \mu^2$, and so $E \cong \sigma$.

Super SAB (Speed up Adaptive Backpropagation) [10] in batch mode was used as learning algorithm to increase the convergence speed during the training process. Evidently, all network variables were normalized to the range (-1, +1).

3. DISTRIBUTION OF INPUT-OUTPUT EXPERIMENTAL PAIRS

When the statistics is small, as it is in this case, the occurrence of overtraining or loss of generalization must be avoided. After the selection of all input-output experimental pairs for each time percentage, it is necessary to separate them in two sets: a training set and a test set. This is usually done by random sorting. The training set is used to update the synaptic weights while the test set is used to measure the neural network performance on an unknown pairs set, during the learning process. As the network only learns what is taught, when the statistics is small a larger number of pairs is usually allocated to the training set. In our case we used 70% of the total number of pairs to the training set.

Generally, as the learning process goes on, the error for the training set continuously decreases, but the error for the test set decreases and then increases: in this second stage the network is said to be overtraining, loosing its capacity to generalize. It is generally accepted that the best network is the one that produced the minimum error for the test set.

The statistical representativeness for both the training set and the test set is a crucial factor to the success of the learning process. The separation of a training set and a test set with high statistical representativeness was a hard task since the first experiments [11], as the available statistics is poor. When the test and training sets are distributed in a random way, they usually lead the learning process to fail. In this case, it is observed that the RMS relative error of the test set decreases and increases very fast, after a small number of computational iterations. We called this behavior *premature overtraining*. Under such condition, the attenuation estimated by the neural network presents poor accuracy.

The analysis of this problem shows that it comes from the existence of regions in the data space very poorly populated. The problem is overcome if a pair in this region is obligatory located to the training set: again, the network only learns what was taught.

To solve the problem, consider each j-th input-output pair is represented in the data space by a vector $\vec{x}_j$ whose components are the inputs *and* the output of the pair.

In a first step those vectors are arranged in classes. The center $\vec{c}_i$ of the i-th class is the mean value of the vectors $\vec{x}_j$ that belongs to the class.

We used a modified version of the Divisive Hierarchical Clustering Algorithm [12]. As our main goal is to hold with classes with an adequate population, class splitting is applied to highly populated classes until the number of individuals in each class is adequate, in our case approximately 6. When the population is conveniently distributed and the number of classes established, the classification is refined: each vector $\vec{x}_j$ is eventually relocated to another class such that the total dissimilarity J, i.e., the sum of the distances between each vector $\vec{x}_j$ and the center of its class $\vec{c}_i$ is minimized.

$$J = \sum_{\forall \vec{x}_j} \left\| \vec{x}_j - \vec{c}_i \right\|^2 \qquad (4)$$

In the second step, the location of each pair to the training or the test sets is made independently for each class. For each class an histogram of the distances between each vector $\vec{x}_j$ allowing to the class and the class center $\vec{c}_i$ is done. Vectors far away from its class center are obligatory located to the training set. Also, classes with very few elements have all its elements allocated to the training set. The other vectors of each class are them randomly sorted, class by class, between the training and test sets to provide the established sets percentage.

Using this procedure we train the largest possible data domain, and don't test in regions that were not trained. After the implementation of this process, no more *premature overtraining* was observed and the neural network performance was considerably improved.

4. RESULTS

To judge the merit of the neural model a comparative analysis with the phenomenological models was carried out for eight different values of time percentage, 0.001, 0.002, 0.003, 0.005, 0.01, 0.02, 0.03 and 0.05%. Figures 2, 3 and 4 show respectively the mean, the standard deviation and the RMS value of the squared relative error evaluated for all input-output experimental pairs (training set plus test set). The analysis was performed for the experimental from UIT-R data with frequencies between 11 and 20 GHz. As shown in fig. 2, the mean error for phenomenological models ranges from 0 to 15% while for the neural model it ranges from 4 to 7%. Fig. 3 shows that the neural network achieved a standard deviation from 15 to 20% while for the phenomenological models it ranges from 30 to 40%. The standard deviation is considered the most important statistical parameter to access prediction model's performance. Finally, fig. 4 shows that the demerit factor proposed by UIT-R, the RMS relative error, ranges from 30% to 40% for the phenomenological models, and from 15 to 20% for the neural model. Therefore, the neural network seems able to predict the rain attenuation with good accuracy, much better than the phenomenological models.

5. CONCLUDING REMARKS

After this analysis it seems reasonable to conclude that a neural network carefully and specifically designed and trained may be used with success to evaluate the rain attenuation in earth-space paths for frequencies between 11 and 20 GHz. The proposed neural network topology and learning process were adequate to the problem. Mainly, a method to reduce the problems caused by data regions with very low statistics, allowing a statistically robust data distribution was proposed and applied with success. This method creates an insight on the data statistical structure and is able to separate them into adequate training and test sets.

The neural network presented an RMS relative error from 15 to 20% while for the phenomenological models it ranges from 30 to 40%, that seems to be a significant performance increase. New studies are currently being carried on in order to extend this meth
od to rain attenuation prediction for frequencies above 20 GHz (Ka Band).

6. REFERENCES

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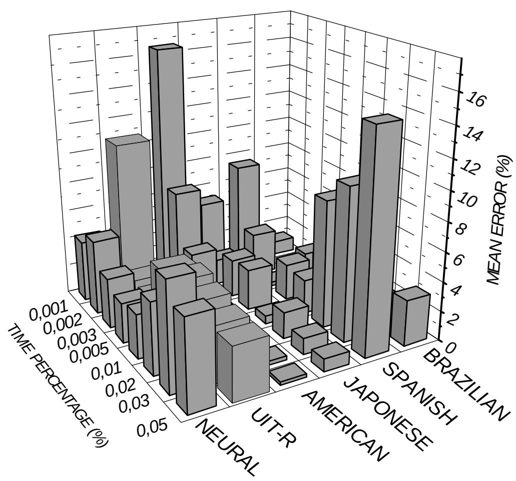

Figure 2: Mean relative error evaluated over all input-output pairs.

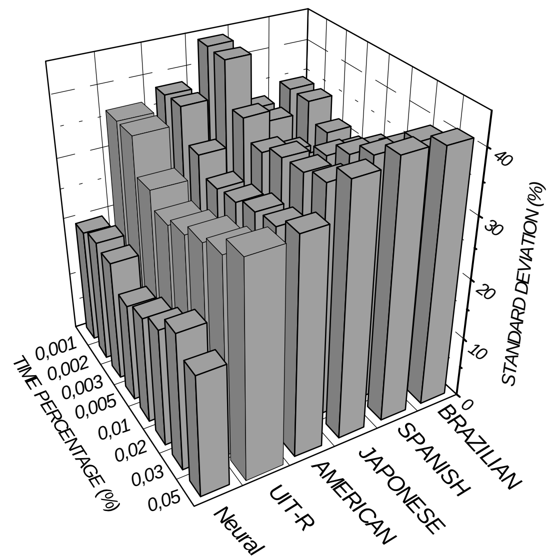

Figure 3: Standard deviation of squared relative error evaluated for all input-output pairs.

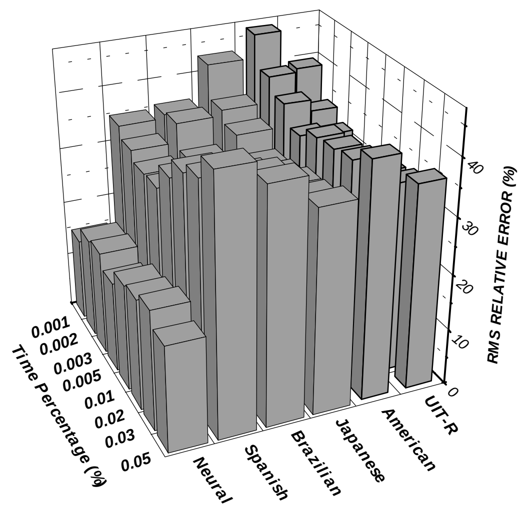

Figure 4: RMS relative error evaluated for all input-output pairs.