EARTH-SPACE RAIN ATTENUATION MODEL BASED ON EPNET-EVOLVED ARTIFICIAL NEURAL NETWORK*

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ABSTRACT

This paper presents a new rain attenuation model, i.e. EPNet-evolved artificial neural network (EPANN) model. EPNet is used in this paper to evolve artificial neural networks that represent the nonlinear relation between rain attenuation and the factors affecting attenuation due to rain. After lots of evolutionary processes, an optimal rain attenuation model based on EPANN is established. The prediction of the model proposed in this paper is compared with that of the ANN model and CCIR model. The results show that applying the EPNet to optimize the rain attenuation model makes a simpler and more accurate model.

Key words: Rain attenuation; Rain attenuation prediction; Artificial neural network; Evolutionary algorithm.

1. INTRODUCTION

Attenuation due to rain becomes a very important problem on the communication system working at frequencies above 10GHz. To predict rain attenuation from known rain rate is therefore essential for design reliability and validity of communication system. The prediction of rain attenuation is a very complex and difficult task. Generally, the prediction models can be either theoretical (also called deterministic), or empirical (also called statistic), or a combination of these two. The theoretical models are accurate, but usually require a great database of radio meteorology characteristics, which is nearly impossible to obtain in most cases. The empirical models are easy to use while the accuracy is unsatisfactory. A compromise is made by the methods of CCIR, Crane and so on, which are accurate in average as well as simple and therefore, main approaches applied in communication engineering [1]. To improve accuracy of rain attenuation prediction further more, many literatures corrected the existed models through using local experimental data [2-4], or promoted new models [5-8], though most of these models can hardly obtain consistent accuracy over the global area. For many years, nearly all of these models have been based on the corresponding relation between rainfall rate R_p and rain attenuation rate γ as $\gamma = aR_p^{\,b}$. Unfortunately, rain attenuation is nonlinearly affected by several complex factors. Due to the assumptions in establishing rain attenuation model based on the relation $\gamma = aR_p^{\,b}$, there needful existed theoretical error in the models themselves and it is hard to predict rain attenuation accurately with those models.

A new and effective rain attenuation model based on artificial neural network (ANN) was proposed firstly in our earlier study [9], which showed that artificial neural network can obtain properly the nonlinear relation between the rain attenuation and the composition of the other factors affecting rain attenuation, and therefore improve the accuracy of rain attenuation prediction compared with other models such as CCIR model. However, because the earlier job used feedforward ANN and backpropagation (BP) training algorithm which method is susceptible to trap in a local minimum of error function and only investigates restricted topological subsets rather than the complete class of network architectures, the previous study might just propose a good model of rain attenuation prediction but not an optimal.

Recently, research on combination of artificial neural networks (ANNs) and evolutionary search procedures, such as genetic algorithm (GA), evolutionary programming (EP) and so on, has attracted a lot of attention. A prominent feature of the combination is that ANNs evolve towards the fittest one in a task environment without outside interference and therefore eliminate the tedious trial-and-error work of manually finding an optimal (fittest) [10]. Among several of evolutionary systems, EPNet is basically the best candidate for evolving feedforward ANN [11]. This paper uses EPNet to evolve ANN model of earth-space rain attenuation and proposes an optimal model based on EPNet-evolved artificial neural network (EPANN), which model is simpler in architecture and more accurate in prediction than the latest rain attenuation ANN model.

In the following, section 2 introduces the algorithm using EPNet to evolve ANN. The architecture and realism of the rain attenuation model based on EPANN are fully described in section 3. In section 4, EPANN model is evaluated as well as compared with ANN model and CCIR model. Finally, section 5 summarizes the results of our study.

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2. EPNet

EPNet is a new evolutionary system for evolving feedforward ANN. It combines the architectural evolution with the weight learning. The main steps of EPNet evolving ANN are introduced in [11]. The major problems and the methods to deal with them in this paper are described as follows：

A. Encoding Scheme for Feedforward ANN: Two equal size matrices and one vector are used as the direct encoding scheme to represent ANN architecture and connection weights (including biases). One matrix is the connectivity matrix of the ANN, whose entries can only be zero or one. The other is the corresponding weight matrix whose entries are real numbers. The entries in the hidden node vector can be either one, i.e.. the node exists, or zero, i.e.. the node does not exist.

B. Fitness Evaluation and Selection Mechanism: The fitness of each individual in EPNet is solely determined by an error value defined by (1) over a validation set containing T patterns

$$E = \frac{1}{T-1}\sum_{t=1}^{T}\sum_{i=1}^{n}(Y_i(t) - Z_i(t))^2 \tag{1}$$

where n is the number of output nodes, $Y_i(t)$ and $Z_i(t)$ are actual and desired outputs of node i for pattern t. The selection mechanism used in EPNet is rank-based. The $(M-j)$ th individual is selected with probability

$$p(M-j) = \frac{j}{\sum_{k=1}^{M} k} \quad (M \text{ is the population size.})$$

C. Replacement Strategy: In EPNet, if an offspring is obtained through further BP partial training, it always replaces its parent. If an offspring is obtained through SA training, it replaces its parent only when it reduces its error significantly. If an offspring is obtained through deleting nodes/connections, it replaces the worst individual in the population only when it is better than the worst. If an offspring is obtained through adding nodes/connections, it always replaces the worst individual in the population.

D. Hybrid Training: The only mutation for modifying ANN's weights in EPNet is implemented by a hybrid-training algorithm consisting of an MBP and an SA algorithm. During BP training, a simple heuristic is used to adjust the learning rate for each ANN in the population and the error E is checked after every k epochs, where k is a parameter determined by the user. If E decreases, the learning rate is increased by a predefined amount. Otherwise, the learning rate is reduced. In the latter case, the new weights and error are discarded. The extra training is performed by an SA algorithm when BP training can't improve the ANN. When the SA algorithm also fails to improve the ANN, four mutations will be used to change the ANN architecture.

E. Architecture Mutation:

Hidden Node Deletion: Certain hidden nodes are first deleted uniformly at random from a parent ANN. Then mutated ANN is partially trained by the MBP.

Connection Deletion: Certain connections are selected probabilistically for deletion according to their importance. The importance is defined by a significance test for the weight's deviation from zero in the weight update process. Denote the weight update $\Delta\omega_{ij}(\omega) = -\lambda[\partial L_t / \partial\omega_{ij}]$ by the local gradient of the linear error function L ($L = \sum_{t=1}^{T}\sum_{i=1}^{n}|Y_i(t) - Z_i(t)|$) with respect to example t and weight ω_{ij}, the significance of the deviation of ω_{ij} from zero is defined by the test variable

$$test(\omega_{ij}) = \frac{\sum_{t=1}^{T}\xi_{ij}^{t}}{\sqrt{\sum_{t=1}^{T}(\xi_{ij}^{t} - \overline{\xi_{ij}})^2}} \tag{2}$$

Where $\xi_{ij}^{t} = \omega_{ij} + \Delta\omega_{ij}^{t}(\omega)$, $\overline{\xi_{ij}}$ denotes the average over the set ξ_{ij}^{t}, $t = 1, \cdots T$. Equation (2) can also be used for connections whose weights are zero, and thus can be used to determine which connections should be added in the addition phase. Similar to the case of node deletion, the ANN will be partially trained by the MBP after certain connections have been deleted from it. If the trained ANN is better than the worst ANN in the population, the worst ANN will be replaced by the trained one and no further mutation will take place. Otherwise node/connection addition will be attempted.

Connection and Node Addition: Certain connections are added to a parent network probabilistically. They are selected from those connections with zero weights. The added connections are initialized with small random weights. The new ANN will be partially trained by the MBP and denoted as Offspring 1.

Node addition is implemented through splitting an existing hidden node. The nodes for splitting are selected uniformly at random among all hidden nodes. Two nodes obtained by splitting an existing node i have the same connections as the existing node. The weights of these new nodes have the following values

$$\omega_{ij}^{1} = \omega_{ij}^{2} = \omega_{ij},\ i \geq j\ ; \omega_{ki}^{1} = (1+\alpha)\omega_{ki},\ i < k\ ; \omega_{ki}^{2} = -\alpha\omega_{ki},\ i < k$$

Where ω is the weight vector of the existing node i, ω^1 and ω^2 are the weight vectors of the new nodes, and α is a mutation parameter which may take either a fixed or random value. For training examples that were learned correctly by the parent, the offspring needs little adjustment of its inherited weights during partial training.

The new ANN produced by node splitting is denoted as Offspring 2. After it is generated, it will also be partially trained by the MBP. Then it has to compete with Offspring 1 for survival. The survived one will replace the worst ANN in the population.

3. STRUCTURE AND REALISM OF THE RAIN ATTENUATION MODEL BASED ON EPANN

A. Inputs and output of ANN: The main factors affecting earth-space path rain attenuation are shown in Fig.1. Under the consideration of the factors above, 8 inputs of ANN have been selected. One group of the inputs has been chosen to take into account the effects of radio parameters on the rain attenuation, including frequency f (GHz), elevation angle θ (degree) and polarization angle ψ (degree). The second group of inputs contains latitude $Lat.$ (degree), longitude $Log.$ (degree), altitude h_a (km) and height h_s (km) of the earth station, which are intended for taking into account the terrain effects on the attenuation due to rain. The last group of inputs is rainfall rate R (mm/hour), which is the main meteorological factor affecting rain attenuation. In fact, there are some other factors affecting rain attenuation such as size distribution of raindrop [12-13]. Considering that it is very difficult to provide neural network with proper information about size distribution, we don't choose them as inputs of neural network, but expect that neural network automatically learn and remember its effect on attenuation due to rain from the meteorological and terrain information of inputs, and then predict rain attenuation perfectly.

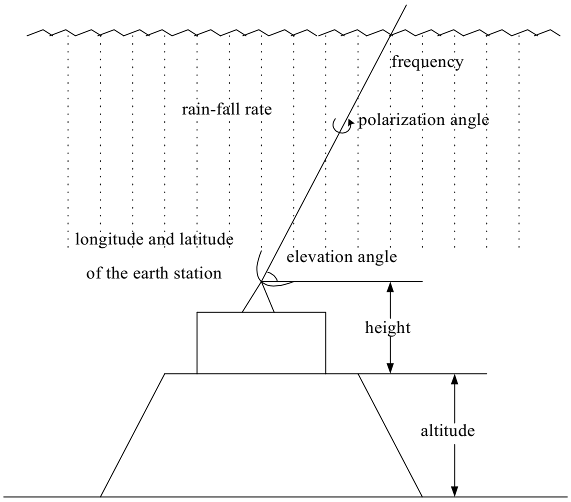

Fig.1 *A slant path affected by rain attenuation*

B. Rain Attenuation Data Set: The data set used for neural network, which is from the CCIR data bank [14] and contains most of the earth-space rain attenuation measurement data since 1972, has 2707 input/output pairs (one input/output pair consists of 8 inputs and one output). This data set has been split into three sets. The first set has been used for training neural network (called training set) by MBP, the second set (validation set) used for evaluate the fitness of the ANN, and the last set (testing set) used for estimate the prediction performance of the best ANN evolved by EPNet. 200 input/output pairs are chosen as testing set by randomly selecting them from the data set. The other 2507 input/output pairs are partitioned into two parts, 1303 used for training set and 1204 used for validation set. Input and output parameters are all rescaled linearly to between 0.1 to 0.9.

C. Experimental Setup: Most parameters used in the experiments were set as follows: the population size (30), the initial connection density (1.0), the initial learning rate (0.25), the range of learning rate (0.1 to 0.7), the number of epochs for the learning rate adaptation (5), the number of mutated hidden nodes (1), the number of mutated connections (1 to 3), the number of temperatures in SA (5), and the number of iterations at each temperature (100). The number of hidden nodes for each individual in the initial population was chosen from a uniform distribution within certain range of 10 to 35. The number of epochs (K_0) for training each individual in the initial population is determined by two parameters: the "stage" size and the number of stages. A stage includes a certain number of epochs for MBP training. The two parameters mean that an ANN is first trained for one stage. If the error of the network reduces, then another stage is executed, or else the training finishes. This step can repeat up to the-number-of-stages times. The two parameters are 500 and three. The number of epochs (K_1) for each partial training during evolution was determined in the same way as the above. The two parameters were 50 and 3. The number of epochs for training the best individual on the combined training and testing data set was set to 2000. A run of EPNet was terminated if the average error of the population had not decreased by more than a threshold value ε (0.05) after consecutive G_0 (10) generations. All the parameters above were chosen after some limited preliminary experiments.

Table 1: *Architecture of EPANN*

	Mean	Std Div	Min	Max
Number of generation	240.6	9.3	190	370
Number of Connections	235.8	8.5	196	421
Number of Hidden Nodes	19.6	2.1	17	25
Error on Training Set(dB)	2.358	0.541	2.177	2.794
Error on Testing Set(dB)	1.805	0.419	1.436	1.947

Table 2: *Comparison of Prediction Error of EPANN Model, ANN Model and CCIR Model*

Model	Mean(dB)	Std Div(dB)	Max(dB)
EPANN	1.28	1.72	3.69
ANN	1.39	2.01	4.7
CCIR	1.98	2.70	7.4

Table 1 shows the average results of EPNet over 30 runs. The error in the table refers is defined by (1). Comparing to the best ANN with 14-14 hidden nodes proposed in the earlier study [9], ANNs evolved by EPNet are more accurate and simpler. This demonstrates that unlike BP training algorithm, EPNet can often discover the optimal ANN. We choose the best among all of the ANNs evolved by EPNet and further train it using MBP on the combined training and validation set. The ANN obtained after that is used as the final rain attenuation model (EPANN model).

4. PREDICTION OF EARTH-SPACE RAIN ATTENUATION

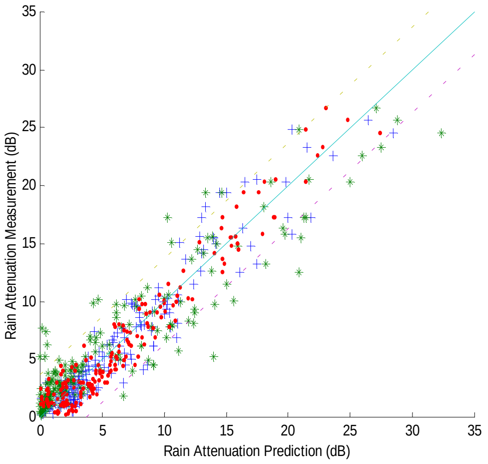

Fig2. *The Comparison of Prediction of EPANN Model, ANN Model and CCIR Model with Measurement*

We compare EPANN model with ANN mode [9] and CCIR model [15] over the same testing set not taken into account during the evolving process. The prediction results are shown in Fig.2., in which "." represents the prediction result of EPANN model, "+" represents the prediction result of ANN model and "*" represents the prediction result of CCIR model. We can see from the figure that the prediction results of EPANN model, ANN model and CCIR model are all close to the 45 degrees diagonal, but the results of the first model is closest than the others, which means EPANN model predicts rain attenuation most accurately.

In order to evaluate the quality of the EPANN model obtained in this paper, we define the prediction error as the absolute value of the difference between the measured and the predicted attenuation value in the same condition. In engineering, such definition of prediction error makes more sense than the definition in [9]. We compute the prediction error of the EPANN model and compare it with the ANN model and the CCIR model and the results are shown in Table 2, where each of the models is tested over the same testing set. It is easy to see from the table that the EPANN model showed satisfactory, even better accuracy.

5. CONCLUSION

A proper system design requires accurate and reliable radio channel model, of which the rain attenuation model is very important. In this paper, a new rain attenuation model based on EPANN is presented. The model not only approximates accurately the nonlinear relation between rain attenuation and other factors affecting rain attenuation, which overcomes some important disadvantages of the traditional models, but also obtains simpler architecture and better generalization ability than the BP-based ANN model proposed recently. The experimental results show that it is feasible to use EPANN to approximate the rain attenuation model. In comparison with ANN model and CCIR model, the EPANN model showed the optimal performance.

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