A GENETICALLY TRAINED NEURAL NETWORK FOR PREDICTION OF PATH LOSS IN OUTDOOR MICROCELL

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ABSTRACT

The various mobile communication networks require the prediction of wave propagation related parameters to predict the pathloss in the particular region of the network. In this paper AI is applied to predict the pathloss in metropolitan and suburban areas. We use genetically trained neural networks to predict the path loss in small-cell network configurations especially microcells and pico-cell. This will help proper cellular system design and better services. In this paper the path loss in outdoor microcell environment of suburban areas and metropolitan centers is determined by the Genetically trained Neural Networks.

Keywords: GA, ANN, Pathloss


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1. INTRODUCTION

The major design consideration of a cellular system depends on the pathloss. The pathloss occurs due to the type of terrain and reflection of the signal from the obstacles. The transmission path between the transmitter and the receiver may be line of sight or may vary depending on the obstacles like buildings, mountains & foliage. The electromagnetic wave propagates either by reflection, diffraction or scattering. Due to the different obstacles present in the path, multiple reflections occur and the electromagnetic wave travels through different paths. This causes multipath fading at a specific location and the strength of the wave decreases as the distance between the transmitter and the receiver increases. If the receiver happens to be located in a deep fade this will result in a substantial decrease in signal strength [1].

Major factors which affect the signal strength at any given location are the transmitter location, height of the transmitter and receiver antenna, power and carrier frequency, the topography of the terrain between the transmitter and receiver in the signal path. Fading can produce major, variations in signal strength relative to the mean level at any location fades it is caused by interference effects due to, multiple propagation paths between the transmitter and
receiver. If the receiver happens to be located in a deep fade this will result in a substantial decrease in signal strength. If the receiver is moving the signal strength received may fluctuate and may pass through several fade regions. These can have different effects on overall system performance. So there has to be a technique or method by which the signal strength will be tested. Many propagation models have been developed. Microcell environment has substantially increased with advent of PCS. This has led to setting up smaller frequently used base stations.

In the recent years, a computer-aided design approach based on neural networks has been introduced for microwave modeling, simulation, and optimization [2]. The genetically trained neural model development design has some important issues like data generation, scaling, neural network training, and testing. The ability of the data to learn from its data and environment has enhanced the application of neural networks in all fields. Here the data or the inputs that are given to the neural network are trained towards the target. So here mapping between the inputs and the targets takes place to determine the optimized weights and bias. Hence this is treated as a mapping formation problem and is accomplished by a multilayer perception (MLP) trained in the back propagation mode [3].

In this paper genetically trained artificial neural networks are used to predict the path loss in outdoor microcells.

2. PROBLEM FORMULATION

The prediction of electromagnetic wave propagation is of great importance in the design and planning of a cellular network both for mobile and wireless-access systems. The path loss in an area depends on factors like the frequency, distance between the transmitter and receiver. A prediction, based on theoretical models, is really valuable since it offers the capability of determining optimum base locations, in order to obtain suitable data rates, to estimate their coverage and evaluate the quality of the wireless network without the need of expensive and time consuming measurements.

The genetically trained neural network takes the parameters like height of the base station antenna height, mobile station antenna height, carrier frequency, environment type and transmission distance between the transmitter and receiver as input to the neural network and gives the amount of pathloss as the output. In the absence of experimental facility, the pathloss for these different parameters are determined by the COST231 HATA model [1]. The input and output parameters are used to train the Genetically trained neural networks. The data has been generated by the help of COST231 HATA model. The pathloss has been predicted for a range of carrier frequency 1500 to 2000MHz, base station antenna height ranging from 30m to 200m, mobile station antenna height ranging from 1m to 10 m. The transmission distance ranges from 1km to 20km.

2.1. Structure of the Genetically Trained Neural Network

The genetic algorithms and neural network can be combined in several ways. Genetic algorithm has been used to:
Generate the weights of a neural network
Generate the architecture of a neural network
Generate both the architecture and weights of a neural network
In this paper weights of a neural network are generated by using Genetic Algorithm. The process is as follows.

The population generated was 40 in number. The length of the chromosome is equal to \((l+m+n)d\) where \(l\) is the no of neurons in the input layer, \(m\) is the no of neurons in the hidden layer, \(n\) is the no of neurons in the output layer and \(d\) is no of digits to be randomly generated. Depending on the neural network structure the length of the chromosome is determined. The weights are extracted from the chromosome and are rearranged into matrix form, as the weights of the ANN model. For each chromosome the weights are extracted and the fitness value of the chromosome is determined by [3]

Let \(x_1, x_2, \ldots, x_d, \ldots, x_l\) represent a chromosome and \(x_{ld+1}, x_{ld+2}, \ldots, x_{(k+1)d}\) represents the \(k\)th gene \((k \geq 0)\) in the chromosome [3].

\[
\begin{align*}
\omega_k &= \begin{cases} 
+ \left( x_{ld+k}10^{-d} + x_{ld+k+1}10^{-d-1} + x_{ld+k+2}10^{-d-2} + \cdots + x_{ld+kd} \right), & \text{if } 10^5 \leq x_{ld+k} \leq 9 \\
- \left( x_{ld+k}10^{-d} + x_{ld+k+1}10^{-d-1} + x_{ld+k+2}10^{-d-2} + \cdots + x_{ld+kd} \right), & \text{if } 10^0 \leq x_{ld+k} \leq 5 
\end{cases}
\end{align*}
\]

After extraction of weights the fitness function must be devised for each problem. Here fitness function is given by:

\[
\rho_i = \frac{1}{E}
\]

Where

\[
E = \sqrt{\frac{\sum_i E_i}{N}}
\]

\[
E_i = \sum_j \left( T_{ij} - O_{ij} \right)^2
\]

and

\(T_j\) is the target output and \(O_j\) is the output vector calculated by the back propagation algorithm. The target here is the pathloss and output \(O_j\) is the predicted pathloss. The extracted weights were initialized to the neural network and the back propagation training was performed to reduce the error. After the training is over the updated weights became the population. crossover and mutation is performed over the population. Now the new population is again given to the neural network after the weights were extracted for training. In this process optimized weights are extracted and error between the pathloss theoretically and the predicted pathloss by the genetically trained neural network is reduced.

The Genetically trained Neural Network model trained with the parameters as mentioned in Table-1.
Table 1 Genetically Trained Neural Network Parameters For Metropolitan Area

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input neurons</td>
<td>5</td>
</tr>
<tr>
<td>Number of output neurons</td>
<td>1</td>
</tr>
<tr>
<td>Number of neuron in hidden layer</td>
<td>1</td>
</tr>
<tr>
<td>Learning rate (h)</td>
<td>.10</td>
</tr>
<tr>
<td>Training tolerance</td>
<td>0.9</td>
</tr>
<tr>
<td>Training time</td>
<td>1 X 10^{-6}</td>
</tr>
<tr>
<td>Training Algorithm</td>
<td>2 min</td>
</tr>
<tr>
<td></td>
<td>Resilient backpropagation</td>
</tr>
</tbody>
</table>

It is observed that less number of hidden layers and neurons are needed.

Table 2 Training Parameters for suburban area

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input neurons</td>
<td>5</td>
</tr>
<tr>
<td>Number of output neurons</td>
<td>1</td>
</tr>
<tr>
<td>Number of neurons in hidden layer</td>
<td>14</td>
</tr>
<tr>
<td>Learning rate (η)</td>
<td>0.1</td>
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<tr>
<td>Training tolerance</td>
<td>1 × 10^{-3}</td>
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<tr>
<td>Training time</td>
<td>4 min.</td>
</tr>
<tr>
<td>Training Algorithm</td>
<td>Resilient backpropagation</td>
</tr>
</tbody>
</table>

The training of the GANN is done by setting the inputs and train them towards the target using MATLAB. The weights and bias obtained after the training to the desired accuracy are the optimized weights that can produce results at par with the theoretical results.

After the training of the GANN the performance of the model is tested for the accuracy of the output with respect to the target. If the desired accuracy is achieved then the model is finalized and the corresponding weights and bias generated are extracted.

3. RESULTS

The GANN is trained and tested for the results. The pathloss is compared for both models at different separations of the base station antenna and the mobile station antenna. The comparisons were made for both the suburban and metropolitan area. The results are at par with the results of the empirical models. Comparative study of pathloss predicted by GANN model and the empirical formula of COST231 HATA model for a carrier frequency of 1500MHz, Base station antenna of height 30m, mobile station antenna of height 1m separated at different distances ranging from 1km to 20km for a metropolitan area and suburban area was made. The results of the GANN are at par with the output of the empirical formula.
Figure 1 Comparative study of GANN output and empirical output for outdoor microcells in a metropolitan area

Figure 2 Comparative study of GANN output and empirical output for outdoor microcells in a suburban area

4. CONCLUSION

The GANN model used for prediction can be trained for a particular region and the respective models can be developed. The neuro model generated for prediction of pathloss has been developed and we can use this for predicting pathloss with going through the Mathematics involved in it. The results are in excellent agreement with the results of the empirical models. Hence it can be further used for design and planning of outdoor microcells.

REFERENCES

A Genetically Trained Neural Network for Prediction of Path Loss in Outdoor Microcell


