Application of Artificial Neural Networks for path loss prediction in railway environments

Speaker : Hong Cheng

Advisor: Prof. Hyukjoon Lee

CINe Lab., Dept. of CE, KwangWoon University, Korea

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INTRODUCTION

- USE ANN in RAILWAY ENVIRONMENT for PATH LOSS PREDICTION

Importance and Difficulty

The proper radio system design requires the accurate and reliable prediction model. And the path loss prediction is the most fundamental factor.

An accurate estimation of path loss provides a basis for proper determination of the field strength , SNR and CIR .

To predict the propagation path loss is a difficult and complex task .

INTRODUCTION

method	principle	advantages	disadvantages
Empirical models	derived from measurement	satisfying computational efficiency	1. field works are very cumbersome and tedious ; 2. not very specific ; 3. can not be used in different environment without modification
Deterministic models	based on the ray tracing technology	more site-specific	1. suffer from the excessive computational time 2. need detailed environmental information

ANN(Artificial Neural Network)

Interpolation, Data Clustering, Pattern Recognition and Forecasting

Solve nonlinear function approximation problems in path loss predictions

Achieve balance between the precision and generality

The intrinsic parallelism allowing for a fast evaluation of solutions

Path loss in railway environment

network	Public	Railway
environments	Urban and hilly scenarios	Viaduct ,cutting and plain

More flat-level environments are needed for safe and fast moving , which leads to the differences in the main propagation mechanisms from public network environments






MEASUREMENT DESCRIPTION

- How to set up the measurement

The description of data source

The data

is based on

the measured results

obtained from the

Zhengzhou-Xi'an express railway line.

The path loss measurement was carried out based on

the received field strength

on the receivers, which is sent from the base station.

The base stations

are placed **every 3 km or so.**

The carrier frequency

was set at the order of

930 MHz

in this paper.

Then the obtained data set in each railway section line was split into

two sets.

The first set (**training set**) was used to network training. The second set (**validation set**) was used to evaluate the performance of the learned network.

The formula of the measured path loss

$$Lp = P_T + G_T + G_R - L_f - L_i - P_R$$

Terminology		
P_T	the transmitted power	43 dBm
G_T	the gain of the transmitting antenna	17 dBi
G_R	the gain of the receiving antenna	
L_f	the loss of the feeder line	3.5 dB
L_i	the insertion loss	3.3 dB
P_R	the received power	obtained from the receiver

ARCHITECTURE OF ANN MODEL

- Description of ANN
- ANN Model Design

Description of ANN

ANN Types

- Back propagation
- Radial basis function

Application Scenarios

- Pattern recognition
- Image progressing
- Forecasting
- Automatic control

BPN Back Propagation Network

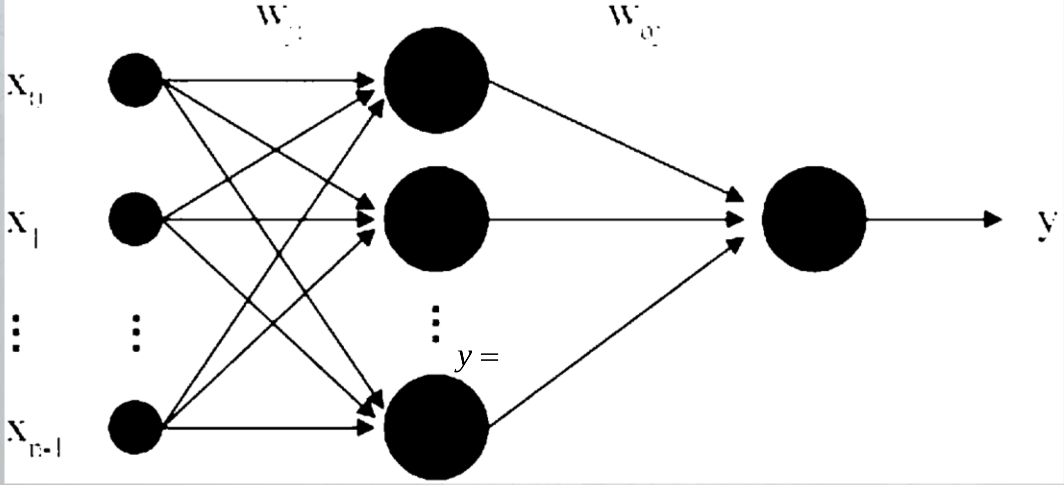
1. Sigmoid activation functions

- Solve problems with mild nonlinearities on the set of noisy data
- Fully corresponds to the field strength prediction

2. Architecture of a typical BPN

- Three or more successive layers or group of basic units called neurons, nodes, or progressing elements , which are fully or partly interconnected to other progressing elements in the same or different layers multiplied by connection weights and added by threshold values.

Description of ANN ~~Rough typical architecture of BPN



Input Layer **Hidden Layer** **Output Layer**

Figure 1

$$y = F_0\{\sum_{j=0}^{M} w_{oj}(F_h(\sum_{i=0}^{N} w_{ji}x_i))\}$$

Description of ANN ~~Rough typical architecture of BPN

$$y = F_0\{\sum_{j=0}^{M} w_{oj}(F_h(\sum_{i=0}^{N} w_{ji} x_i))\}$$

Terminology	
x_i	The i^{th} element of the input vector
$F_0\{\cdot\}$	The activation function of the second layer
$F_h()$	The activation function of the first layer
w_{oj}	The synaptic weights from neuron j in the hidden layer to the single output neuron
w_{ji}	The connection weights between the neurons of the hidden layer and the inputs
N	The number of the input neuron
M	The number of the hidden neuron

Description of ANN ~~ the mean squared error E

The systematic parameters, such as weight values, threshold values, are adjusted by the learning process. This learning phase of the network performs based on **the mean squared error E** between predicted and measured path loss for a set of appropriately selected training examples, which is given by:

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2$$

Terminology	
y_i	**the output value calculated by the network**
d_i	**the expected output（the measured value）**

Description of ANN ~~ the limitation of ANN

Firstly, the convergence of the **training process is relative slow** due to the requirement of the stability.

Secondly, the selection of **the learning rate** is important.

Finally, the problem may have **no solutions** even though it is obtainable in theory.

ANN Model Design ~~ distance and normalization

In this model, the **distance** between base station and receiver is selected as the input units of the neural network.

And the output node of the neural network is the received signal strength.

Input and output parameters are **normalized** so that they take values in the range. Normalization is taken from premnmx function in matlab, which is given by :

$$P_n = 2 \times (P - P_{\min}) / (P_{\max} - P_{\min}) - 1$$

- In order to make the **training time** **as short as possible**, the learning parameters, like weight values and threshold values, were selected **in a default way.**

- As a learning rule, **error back propagation** is chosen **since** it provides a computationally efficient method for changing the weights in a back propagation network

ANN Model Design ~~ the learning algorithm selection

Scaled conjugate gradient (SCG) algorithm, Fletcher-Reeves conjugate gradient (FCG) algorithm, quasi-Newton method (QN), **Levenberg-Marquardt (LM) algorithm** and Powell-Beale conjugate gradient (PCG) algorithm

Algorithm	Mean(dB)	Variance|(dB)
SCG	1.19	0.95
FCG	1.20	0.95
QN	1.11	0.90
LM	**1.10**	**0.80**
PCG	1.16	0.92

Terminology	
The relative height of the transmitting antenna	20-40 m
The height of the receiving antenna	3.5 km
The frequency used here	932.8 MHz

The measurements were made in a viaduct scenario in some railway section line.

COMPARISONS

- Comparison Between Proposed Model and Hata Model
- Comparison Between Measurements and Predictions

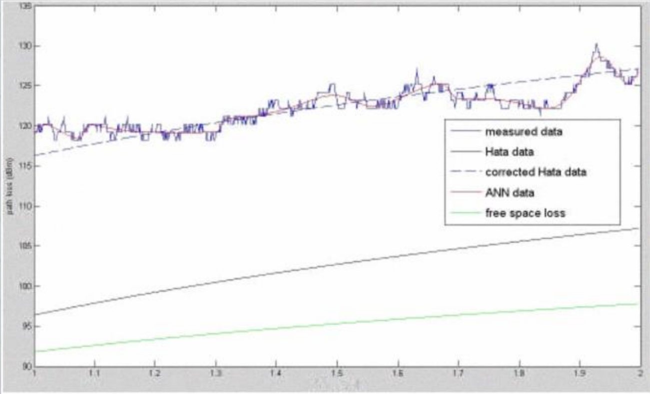
Comparison Between Proposed Model and Hata Model

$$L_p(dB) = 69.55 + 26.16\log f_c - 13.82\log h_b - a(h_m)$$
$$+ (44.9 - 6.55\log h_b)\log d - 4.78(\log f_c)^2$$
$$+ 18.33\log f_c - 40.94$$

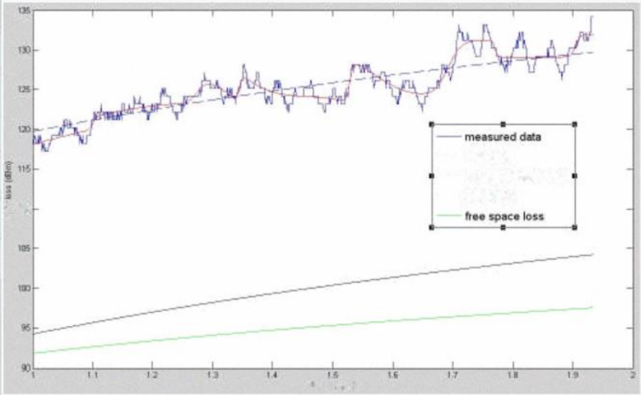
Terminology	
f_c	The frequency(MHz) with the range from 150 to 1500
h_b	The relative height(m) of the transmitting antenna in the base station
h_m	The height(m) of the receiver
d	The distance between the base station and the receiver

$a(h_m) = 3.2(\log 11.75 h_m)^2 - 4.97 \quad for \quad f_c \geq 300MHz$ in a large city

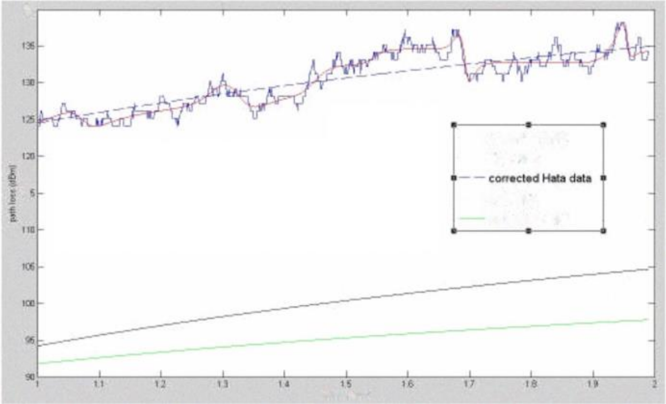
Comparison Between Proposed Model and Hata Model



Viaduct scenario



Cutting scenario



Plain scenario

Comparison Between Proposed Model and Hata Model

Terminology	
The height of the receiver	3.5m
The distance	**1-2km**

During the measurements, because if the distance is less than 1 km at the frequency of about 900MHz, there exists the near-filed effect, which will affect the prediction [2]. And for the distance **less than 1 km** does not affect the network planning, this range is not required to be considered in this case And the distance **more than 2 km** is overlapped with the coverage of another base station. Therefore, just 1-2 km distance was taken into account.

Comparison Between Proposed Model and Hata Model

ERROR STATISTICS FOR PATH LOSS BY HATAANOANN IN DIFFERENT SCENARIOS

Prediction model		Frequency(MHz)	Height(m)	Mean(dB)	Variance(dB)
Viaduct	Hata	932.8	23	19.9	2.9
	Corrected Hata			1.3	1.1
	ANN			0.6	0.2
Cutting	Hata	932.4	33	25.5	3.2
	Corrected Hata			1.4	1.1
	ANN			0.8	0.4
Plain	Hata	932	33	30.3	3.5
	Corrected Hata			1.5	1.1
	ANN			0.8	0.3

Comparison Between Measurements and Predictions

the characteristic of generality

Scenario	Mean(dB)	Variance(dB)
Viaduct 1	1.73	1.70
Viaduct 2	1.2	1.5
Cutting 1	**4.49**	**6.49**
Cutting 2	**3.24**	**7.03**
Plain 1	2.92	2.31
Plain 2	2.39	3.96

Comparison Between Measurements and Predictions

Figure 3. Layout sketch map of railway sections

CONCLUSION AND FUTURE WORK

Conclusion

Conclusively, the ANN-based model can predict the path loss for other similar scenario under certain precision, where no measured data is available.

The predicted results show acceptable agreement with the measured data and validate the generality of the proposed model.

Comparison Between Measurements and Predictions

To predict the path loss in railway environment as accurately and fast as possible, the proposed ANN model is **INTRODUCED firstly** in railway environment, through which **some disadvantages** of both **empirical and deterministic** propagation model can be overcome.

Within the proposed ANN models, environment characteristics can be considered **more easily** than empirical models.
On the other side, the ANN models are **more simple and computationally fast** than deterministic models.

According to the results predicted by the proposed model, the prediction can be **successfully used in railway environment with relatively high precision**.

Comparison Between Measurements and Predictions

The proposed ANN model is based on the popular back propagation network **ARCHITECTURE**.

According to analyses, LM algorithm are chosen for measurement environments.

In **COMPARISON** with other conventional model, more accurate predictions can be achieved using the proposed model after being trained by part of measured data.

And comparisons between measurements and predictions by trained ANN model show that the proposed model can also be applicable in another railway section with the similar scenario.

THANK YOU FOR WATCHING !

Speaker : Hong Cheng

Advisor: Prof. Hyukjoon Lee

CINe Lab., Dept. of CE, KwangWoon University, Korea