Adaptive Neuro-Fuzzy Inference Systems for Indoor Propagation Prediction

S. Phaiboon*, P. Phokharatkul** and S. Somkurnpanich***

*Department of Electrical Engineering, Mahidol University
(Tel : +62-2-8892138; Email: egspb@mahidol.ac.th)
**Department of Computer Engineering, Mahidol University
(Tel : +62-2-8892138; Email: egpph@mahidol.ac.th)
***Department of Electronic, Kingmonkul Institute of Technology Ladkrabang
(Tel : +62-2-7373000; Email: kssuripo@kmitl.ac.th)

Abstract: A new model for the propagation prediction for mobile communication network inside building is presented in this paper. The model is based on the determination of the dominant paths between the transmitter and the receiver. The field strength is predicted with adaptive neuro – fuzzy inference systems (ANFIS), trained with measurements. The advantage of the ANFIS with hybrid least squares and gradient descent algorithms is fast convergence compared with original neural network. The K-means algorithm for selection of training patterns is also used. Comparison of our predicted results to measurements indicate that improvements in accuracy over conventional empirical model are achieved.

Keywords: Indoor propagation prediction, Measurement data, ANFIS

1. INTRODUCTION

NOWADAY, there are two different approaches for the prediction of the field strength inside buildings. On the first hand there are empirical models, based on the regression of measurement data [1]-[2]. These models are very fast and easy to apply in computing the prediction model. However, they would rather suffer with poor accuracy. On the other hand, there are deterministic models like ray tracing [3]-[5]. However, these models are sacrificed with excessive computation time and the requirement of detailed databases. Cheung et al [6] have proposed a new empirical model that is based on the uniform theory of diffraction (UTD) shown the superior accuracy of its prediction. However, the model has problem of accuracy for highly reflective environments because it did not take account of waveguiding effect from the reflected rays. G. Wölfle et al. [7] demonstrated that a neural-based propagation loss model for indoor environment train by a back-propagation algorithms showed the superior accuracy of its prediction. However, the MLP has problem of slow convergence and unpredictable solutions during training.

To solve these problems, this paper presents a means to approximate the indoor propagation loss based on adaptive neuro-fuzzy inference systems (ANFIS) [8]. ANFIS consist of fuzzy rules which are local mappings (which are called local experts) instead of global ones. These local mappings facilitate the minimal disturbance principle, which states that the adaptation should not only reduce the output error for the current training pattern but also minimize disturbance to response already learned. This is particularly important in on-line learning. The ANFIS also use the least-squares method to determine the output of each local mapping is of particular importance. As the results, the prediction with high accuracy and fast convergence can be obtained.

One major advantage of the ANFIS is that hybrid learning algorithm, which can be divided into two pass, like redial basis function (RBF) neural network in which the fast convergence has been guaranteed [8]. In the first pass, the consequent parameters are identified by the least square method under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster since it reduces the searching space dimensions of the original MLP. In the second pass, the error signals propagate backward and the premise parameters are updated by gradient descent under the condition that the consequent parameters are fixed. As the results, the prediction with high accuracy and fast convergence can be obtained.

In this paper, we propose a new formulation for applying the adaptive network based fuzzy inference system in order to improve convergence performance of this hybrid algorithm.

Section II describes the determination of the dominant path. Section III presents the new procedure for the approximation of propagation loss model in indoor environment using the ANFIS. Section IV describes the measurement procedure in the building used to the training and checking data. Section V presents the prediction results and the effectiveness of the ANFIS model. Finally, the paper is concluded in Section VI.

2. PREDICTION OF PROPAGATION PATH LOSS

The first step of the proposed model is to determine the and/or diffracted ray paths going to the receiver would be combined to a dominant path. This dominant path contains only information about the direction of the path, diffraction at the corner and the passed rooms. The algorithm determining of the dominant paths sometime leads to more than one solution. But in most cases only one solution with the smallest path loss is necessary for an accurate prediction and chosen by the minimum of L_T defined as

$$L_T = \min[L_D, L_{DIF}] \quad (1)$$

Where L_T is the total attenuation along the dominant path, L_D and L_{DIF} are distance dependence path loss and diffraction path loss respectively.

A. Distance Dependence path loss L_D

We define the path loss as the function of the distance between the transmitter and the receiver, *d* for the dominant path. This propagation loss has two distinct regions [6]. In the first region, within 0-15 m of the transmitter, the propagation loss is similar to that occurring in free space. This is because the obstructions, such as walls and doors, do not interact significantly with propagation waves at proximal ranges. On the other hand for the distal region, the propagation loss increases significantly as the electromagnetic waves become obstructed by the walls and doors of the rooms in the building. The distance at which this transition in propagation occurs is referred to here as the breakpoint. The distance dependence path loss then follows:

$$\begin{aligned} L_D &= 10 \log\left(\frac{d}{d_o}\right)^{n1} U(d_{bp} - d) \\ &+ 10\left[\log\left(\frac{d_b}{d_o}\right)^{n1} + \log\left(\frac{d}{d_{bp}}\right)^{n2}\right] U(-d_{bp}) \\ &+ \sum_{p=1}^{P} \mathrm{WAF}(p) / \cos\theta p \end{aligned} \qquad (2)$$

Where *do* is the reference distance which is taken here as 1 m from the transmitter, d_{bp} is the distance of the breakpoint from the transmitter, n_1 and n_2 are the path-loss exponents on either side of the breakpoint, and U(·) is the unit step function defined as

$$U(d) = \begin{cases} 0, & d \le 0 \\ 1, & d \ge 0 \end{cases} \qquad (3)$$

WAF(p) is the value of the wall attenuation factor at normal incidence and the θ_p is the angle between the *pth* wall and straight-line path joining the transmitter to receiver.

The parameters d_{bp}, n_1 and n_2 can be obtained from the used of Fresnel zones. By considering the size of the first Fresnel zone, a distance *d* from the transmitter and determining at what distance it will become obstructed the breakpoint d_{bp}, can be calculated by d_{bp}, = 4(H-h_2)h_2/λ [9]. Consequently, in a ceiling 2.5 m height and receiving antenna 1.5 m height, the breakpoint d_{bp} is determined at 36 m for frequency 1800 MHz.

The exponent n_1 generally should be about the free-space value of 2.0 once antenna effects are removed.The parameter n_2 we have found value of 1.7 for propagation along the corridor [9].

B. Diffraction path loss L_{DIF}

In general, wave propagation guided by a corridor will sometime provide an indirect path, which may be significantly greater than the propagation loss from the straight-line path between the transmitter and the receiver. Therefore, the indirect paths are needed to be the dominant paths and determined from diffraction from corners (including door and window frames) in the building. The diffraction path loss is given by

$$\begin{aligned} L_{DIF} = -10 \log\Bigg[&\sum_{m=1}^{M} (\delta_D(d_m)\delta_D(d'_m) \\ &\times \left| D(d_m, \phi_m, d'_m \phi'_m) \right|^2 \Bigg] \end{aligned} \qquad (4)$$

Where M is the number of the corners in the building data base, the subscript *m* refer to *m* th corner, and $\delta_D(\cdot)$ is the dimensionless quantity $10^{-L_D(\cdot)/10}$

3. PREDICTION OF PROPAGATION PATH LOSS

For computation of path loss with ANFIS, the parameters of the minimum loss dominant path in Section II must be determined. Because the dominant paths represent a group of nearly similar rays between the transmitter and the receiver, all relevant parameters of these rays governing propagation should be considered in the description of the dominant path. The parameters of the dominant path will be grouped into fuzzy sets for the ANFIS inputs.

A. Parameters of the dominant path

The prediction with accuracy results have been obtained with the following parameters

1). Free space attenuation along the path L_{FS}

$$L_{FS} = -27.56 + 20\log\left(\frac{f}{\mathrm{MHz}}\right) + 20\log\left(\frac{d}{m}\right) \qquad (5)$$

Where *d* is the distance of the dominant path

2). Wall loss L_W

$$L_W = \sum_{p=1}^{P} \mathrm{WAF}(p) / \cos\theta p \qquad (6)$$

Where WAF(p) is the value of the wall attenuation factor at normal incidence and the θ_p is the angle between the *p th* wall and the dominant path.

3). Angle loss at the corner to the transmitter L_T

$$L_T = \frac{1}{A_k} \sum_{m=1}^{M} AT(m) \qquad (7)$$

Where Ak, AT(*m*) is the normalized factor and angle of changing in the direction of the dominant path along the corridor since corner diffraction relative to the transmitter, M is the number of corners in the building database and *m* refer

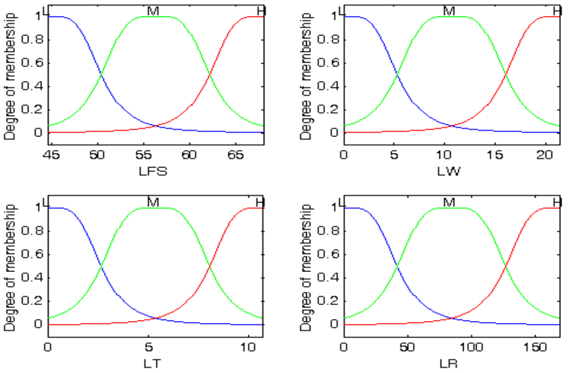

Fig. 1. Fuzzy sets of the input parameters

to the m th corner.

4). Angle loss at the corner to the receiver L_R

$$L_R = \frac{1}{A_k}\sum_{m=1}^{M} AR(m) \qquad (8)$$

Where Ak, AR(m) is the normalized factor and angle of changing in the direction of the dominant path along the corridor since corner diffraction relative to the receiver, M is the number of corners in the building database and m refers to the mth corner.

B. ANFIS architecture for the prediction

The fuzzy inference system under consideration has four inputs and one output The inputs consist of four parameters as considered in part A, each parameter is fuzzified in to three fuzzy sets (for a good model,[8]) namely, L = low, M = medium and H = high, as shown in Fig. 1 We use the generalized bell function for the membership function of the fuzzy sets, which is given by

$$\mu_{Ai}(x) = \frac{1}{1+\left|\dfrac{x-c_i}{a_i}\right|^{2b_i}} \qquad (9)$$

Where $\mu_{Ai}(\cdot)$ is membership function,$\{a_i, b_i, c_i\}$ is the parameter set.

The common rule set for first-order Sugeno fuzzy model with four fuzzy if-then rules is the following

Rule i: If L_{FS} is A_j and L_W is B_j and L_T is C_j and L_R is D_j,
then $f_i = p_iL_{FS} + q_iL_W + r_iL_T + s_iL_R + t_i$.

Where A_j, B_j, C_j, and D_j are fuzzy sets of L_{FS}, L_W, L_T ,and L_R respectively, subscript i=1, 2, 3,….,n, n is the number of rules and subscript j represent fuzzy set L, M, and H for j=1, 2, and 3 respectively, f_i is the path loss output of the fuzzy rule i,

The corresponding equivalent ANFIS architecture is shown in Fig. 2, where nodes of the same layer have similar functions, as following. (we define the output of the j th node in layer as $O_{l,j}$)

1) layer 1

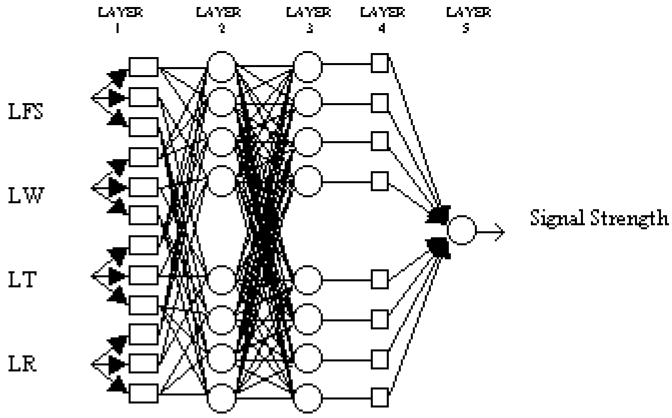

Fig. 2. The equivalent ANFIS architecture

Every node i th this layer is an adaptive node with a node function as follows

$$\begin{aligned} O_{l,j} &= \mu_{Ai}(L_{FS}), && \text{for } i = 1, 2, 3, \text{ or} \\ O_{l,j} &= \mu_{Bi-4}(L_W), && \text{for } i = 4, 5, 6, \text{ or} \\ O_{l,j} &= \mu_{Ci-7}(L_T), && \text{for } i = 7, 8, 9, \text{ or} \\ O_{l,j} &= \mu_{Di-10}(L_R) && \text{for } i = 10, 11, 12 \end{aligned} \qquad (10)$$

The parameters in this layer are called as *premise parameters.*

2) layer 2

Every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signal as follows

$$O_{2,i} = \text{wi} = \mu_{Ai}(L_{FS})\mu_{Bi}(L_W)\mu_{Ci}(L_T)\mu_{Di}(L_R),\ i = 1, 2, 3 \quad (11)$$

Each node output represents the firing strength of the rule.

3) layer 3

Every node in this layer is a fixed node labeled N, The i th node calculates the ratio of the i th rule's firing strength to the sum of all rule's firing strengths as follows

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1,2,3 \qquad (12)$$

The output of this layer are called *normalized firing strengths.*

4) layer 4

Every node i in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_iL_{FS} + q_iL_W + r_iL_T + s_iL_R + t_i) \quad (13)$$

Where $\overline{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i, s_i\}$ is the parameter set of this node. Parameters in this layer are referred to as *consequent parameters.*

5) layer 5

The single node in this later is a fixed node labeled Σ, which computes the overall output as the summation of all

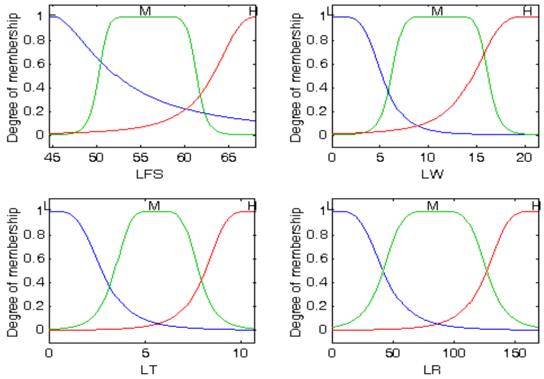

Fig 2. Membership function after learning

incoming signals as follows

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i \overline{w_i f_i}}{\sum_i w_i} \quad (14)$$

C. Hybrid learning algorithm

The ANFIS architecture consists of 5 layers. The parameters in first layer are premise parameters and in layer 4 are consequent parameters [8]. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters, pi, qi, ri, si, and ti, i=1, 2, 3,….,n, n is the number of rules. From this observation, we have three set of parameters, that are 1) Set of the total parameters, 2) Set of premise (nonlinear) parameters, and 3) Set of consequent (linear) parameters. In the forward pass of the hybrid learning algorithm, node output go forward until layer 4 and the consequent parameters are identified by the least squares method. In the backward pass, the error signals propagation backward and the premise parameters are updated by gradient. The consequent parameters which are optimal under the condition that the premise parameters are fixed. At the result, the hybrid approach converges much faster since it reduces the search space dimensions of the original pure back propagation method.

4. TRAINING PATTERNS

A. Measurement procedure and locations

The equipment for propagation measurement consisted of a fixed transmitter and a narrow-band (20KHz) portable receiver with a notebook computer. The fixed transmitter consisted of a network analyzer (with 20 dBm power output) and $\lambda/4$ omnidirectional (2.2 dBi gain) at a height 1.5 m. We used a spectrum analyzer and $\lambda/4$ omnidirectional (2.2 dBi gain) at a height 1.5 m for signal strength measurement.

To receive propagation data for training and prediction, about 431 samples of the actual field at frequency 1800 MHz were acquired on uniform grid (with a grid size of 1 m^2) in a laboratory building area for the training data the checking data. We removed the effects of fast fading at each sample point by the mean value of at least 25 measurement in a 400 cm^2 area centered around the sample point.

The laboratory building of Mahidol University was completed in 1993 and consists of five floors and a dimension of 50 x 50 m^2 . The construction of the building is of concrete block, plaster board, and mirror walls, the floor to floor height is 4 m a suspended ceiling containing air conditioning and service ducts 2.5 m above the floor. The general environment has furniture primarily constructed from wood or metal in office and laboratory spaces.

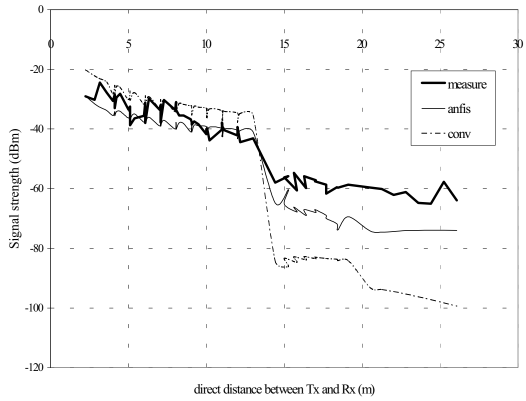

Fig 3. Curve plots of prediction versus measured signal strength

B. Selection of training patterns

Since the statistical distribution of each input parameter of the ANFIS combination of the different input parameters is distributed in a homogeneous way. So the training sometime can not convergence. To avoid this event, an algorithm for the selection of representative training patterns has been used. The method for classification is developed from K-means algorithm.[10] in appendix.

5. PREDICTION RESULTS

In order to compare our method with the conventional empirical model in (2), a set of 431 measurement points taken in the laboratory building was divided into 101 training patterns and 59 checking patterns. By inputting 101 training patterns into the ANFIS network, the training mean-squared error can be found as 0.008 after 5,000 epochs of training while the original MLP training was not converged by the same training patterns. Fig. 2 illustrates the membership functions after training. It is interesting to observe that the curve of the membership functions of L_{FS} are significantly changed since the effect of the free space loss along the corridor. It is fact that if the free space loss is low, the received signal strength is high. But in case of diffraction at the corner along the corridor, the received signal strength has been still high although the free space loss is increased. Accordingly, the membership after training was adjusted in order that the free space loss fall in fuzzy set L.

Next, we would like to verify the approximation capability of the ANFIS-based propagation prediction model by a set of 59 checking patterns. A comparison of curves shown in Fig. 3. The standard deviation in error for the ANFIS model (14) is 6.6 dB while that for the conventional model (2) is 12.1 dB.

It can be observed that the convention model (2) predictions overestimate the actual signal strength by up to 40 dB as shown in Fig. 3. The reason the conventional model performs poorly in this region is because the direct path becomes blocked by the large attenuation of walls between the transmitter and the receiver making the conventional model prediction a small signal strength. The ANFIS model, however, finds that the actual signal strength is high because there is a diffracted path from the corners along the corridors

6. CONCLUSION

In this paper, we have provide a new model for propagation prediction inside the building. It is based on the determination of the defined dominant path between the transmitter and the receiver. The parameters of these paths are then used as input values for ANFIS ,which is trained with measured data. We have also demonstrated that the model has improved accuracy compare to the conventional model in a laboratory building. This is achieved by a proper selection of the training patterns of the ANFIS and a validation of the training progress.

Because of the very small computation time of this approach nearly similar to the empirical models, it is suggests that it is would be really suited for planning the base station position within buildings [11]-[12].

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Appendix

Algorithms of group classification

1) Select *m* patterns from training set, use as the initial centers for each group.

2) Distribute the sample *x* among the *m* groups.

3) Find distance between pattern and mean of each group.

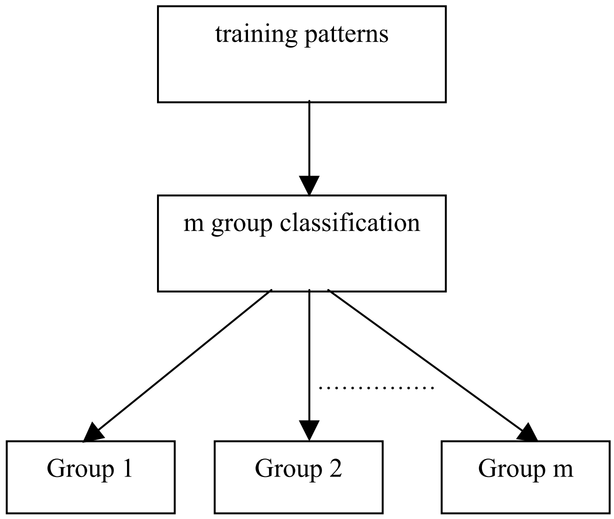

Figure A1. Diagram of the group classification

$$distance(x, g_m) = \sqrt{\sum_{i=1}^{n} (x(i) - M(i))^2}$$

Where x(·), M(·) and n are the value of pattern, the mean value of the pattern in group, and the number of pattern in group respectively

4) If $\min(distance(x, g_m))$ larger than threshold value (here we used 0.06) then we created new group.

5) Therefore, the new cluster center are computed.