Analysis and Prediction of Indoor wireless Propagation Using adaptive Neuro-Fuzzy Inference System

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ABSTRACT

We present an indoor wireless signal strength prediction using adaptive neuro-fuzzy inference system. The study was conducted on the third floor of a five story office building in the Ilupeju area of Lagos State. The test drive was conducted in a fifteen meter closed corridor general office with furniture and other office equipment that may impact the propagation of wireless signals. Wireless signal strength measurements were taken using Cisco Aironet 3602 access point. It has the capability to operate at both 2.4GHz and 5.0GHz radio spectrum. The measurement period was for six months. The minimum mean square error was used to determine the path loss exponent of 2.96. A model equation for the study was developed and can be used to predict indoor path loss had shortcomings and was not able to fit the observed data effectively.

This research focuses on using Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict Wireless Local Area Network (WLAN) received signal strength (RSSI) in an indoor area by training some neurons based on data collected from a drive-test. The drive test used comprised of laptop with wireless network card that are capable of associating to wireless LAN networks on 802.11b, g, and n. An ANFIS model was developed and this was compared with an empirical model. Statistical analysis tools of RMSE and Chi-square goodness of fit were used to compare the models.

(Keywords: RSSI, ANFIS, RMSE, Chi-Square, SNR, Path-Loss)

INTRODUCTION

Due to the high rise in demand for bandwidth as a result of multimedia requirements in Wireless LAN environments, and also the advent of Bring Your Devices to Office (BYOD), effective and efficient methods of predicting signal strength at different locations of the investigated indoor are has to be developed.

IEEE 802.11 wireless local area networks (WLANs) have been widely deployed in many places for both residential and commercial use [1]. The IEEE 802.11 standard supports two major forms; the point coordination function (PCF) and the distributed coordination function (DCF). With PCF, the transmission in the network is based on a central node where the access point device is the central node device [2].

Client nodes (i.e. 802.11 wireless cards in computers and smartphones) listen to the channel and wait for the signal from the access point. Once permission is sent by the access point, the client node can start data transmission. On the other hand, with DCF, the nodes employ carrier-sense multiple-access with collision avoidance (CSMA/CA) for MAC protocol. Each node can transmit independently of one another, based on the availability of the channel resources. In particular, with CSMA/CA, the nodes listen for the channel status. If the channel is busy, the node defers its transmission by waiting for a back-off period. If a node senses a channel is idle, it will wait for a certain period of time and start transmission.

Indoor propagating environment comprises complex geometry obstacles and blockage of line-of-sight path in most cases. The environment is usually made of walls, glass, furniture, and other materials with different conductivity and permeability. Radio waves penetrate these kinds of obstacles in ways that are very hard to predict. Indoor radio signal attenuation rate is affected by path-loss, reflection, diffraction, scattering and multi-path fading characteristics of the propagating environment. Many propagation models have been used to predict and model radio channel characteristics. These models are useful tools in radio network planning and implementation [4], however most of them varies significantly when compared to data from drive test or observed data.

The contribution of this study is to develop a better model that is capable of predicting RSSI values in a particular indoor scenario. Received Signal Strength Indicator (RSSI) and SNR parameters of wireless clients connected to indoor Access Point are recorded. The measured values per varying distances are then stored in database, these data collected over six (6) months is used to train an Artificial Intelligent (AI) prediction systems.

Adaptive Neural Fuzzy Inference System (ANFIS), developed by Math Works is an effective Artificial Intelligent prediction system that uses combination of machine learning technique of Neural Networks and Fuzzy Logic as an alternative approach to learn radio fading/propagation behavior [3]. This study will predict RSSI of an indoor WLAN RF propagation using ANFIS based on received signal strength data of a drive test. The performance of the model developed from this system will be compared with the data collected from the observed data and an Empirical model.

This paper is organized as follows: we present related works and radio channel models and the ANFIS structure and statistical analysis required to compare the model with other existing models. The methodology employed in this study is shown along with our data and analysis, and the conclusions drawn from this study.

RELATED WORK

The performance of wireless LAN system depends mostly on the characteristics of the propagation channel, and the understanding of radio wave propagation is essential in the design and deployment of wireless solutions [9]. It is the characteristics of radio wave propagation that make the deployment of wireless solution more complex than the wired solution. Radio wave propagation is heavily dependent on sites' specific terrain, frequency of operation and interferences between the transmitter and receiver path.

According to work done by (Oguejiofor, et al.) in [2] an empirical mathematical model that predicts the receive signal strength (RSSI) was developed. The model was based on Log-Normal path loss with no account for shadowing or variation effects that can be caused by signal attenuation due to walls, glass clutters, etc. In [18] Ivan Vilovic, and Zvonimir Sipus used a neuron network system to predict RSSI in a particular indoor environment and data from three different access points to train the system. The result was compared with 3-D Ray Tracing deterministic model and a neuron network prediction model was developed.

This study will focus on improving indoor wireless RSSI prediction using a fusion of Artificial Neural Network and Fuzzy Network in 2.4 GHZ frequency band of the indoor wireless system. Radio wave propagation and different models that are applicable to indoor wireless propagation is carried out. Although many of the techniques developed to characterize the outdoor propagation environment can readily apply within buildings [9], but there are still a bit of odds as the indoor environment geometry is more complex and there may not be one solution fits for all.

In order to predict indoor wireless signal strength at the receiver accurately, the path loss models and prediction tools which takes into consideration the geometry of the indoor environment is of high importance. We will introduce Artificial Intelligence techniques focusing on adaptive neuro-fuzzy inference systems [21], in the foregoing.

Prediction models based on artificial intelligence for wireless signal strength has been seen as alternatives to other various type of prediction models such as deterministic, empirical, electromagnetic as well as statistic [4]. The advantages offered by artificial intelligence are flexibility to be used to model different environment and high-speed processing capability.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Recent accomplishments in machine learning algorithms have made AI based prediction models an alternative to predicting signal strength in different indoor and outdoor environments.

Professor Roger Jang (1993) combined two hybrid techniques of Neuro network and Fuzzy logic to propose what is known as Adaptive Neuro-Fuzzy Inference System (ANFIS) [5]. ANFIS, offers useful properties in nonlinearity, adaptability to different radio frequency scenarios, input–output mapping, error tolerance, and ease of simulation [22]. In this combinational design, Fuzzy system represents IF-THEN rules knowledge structure in an interpretative manner and has it's learning ability derived from a Neural network that can fine-tune the membership functions parameters and linguistic rules straight from observed data in order to improve system performance.

Designing an ANFIS system entails establishing the number of inputs, type and number of fuzzy membership function, and the number of epochs. Adaptive Neuro-Fuzzy Inference System starts with learning process; first, a training data set that includes some of the input/output data pairs of target systems is applied to the system. These training data sets are required for ANFIS' fine tuning purposes, at this stage fuzzy rules are generated and the membership functions parameters are fine-tuned using machine learning optimization technique.

The next stage is the testing phase, in the testing stage, testing data set are used to validate that the system can produce equally decent results for new input values, different from those used during training stage [5].

The ANFIS architecture deployed for this study is a five-layer feedforward first-order Sugeno Fuzzy network, using a combination of Gradient Descent and Least Squares Estimator (LSE) algorithms to update the parameters of the networks. There are two sets of parameters updates in ANFIS: premise and consequent parameters.

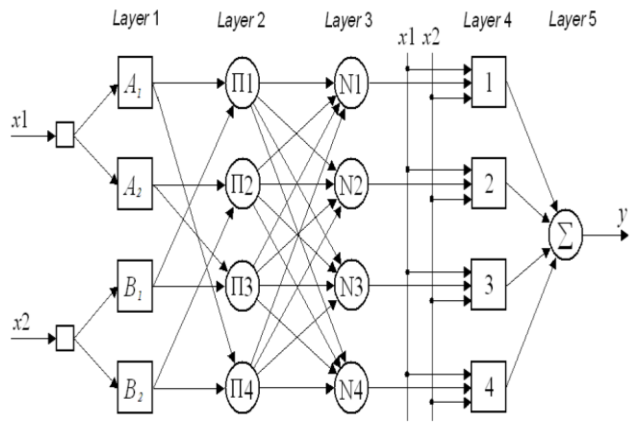

Figure 1: Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993).

From Figure 1 above, considering a first-order Sugeno Fuzzy inference system, with two crisp input x_1 and x_2 and one output y. The two Fuzzy rules would be as below:

Rule 1: If x_1 is A_1 and x_2 is B_1, then $f_1 = p_1 x_1 + q_1 x_2 + r_1$

Rule 2: If x_1 is A_2 and x_2 is B_2, then $f_2 = p_2 x_1 + q_2 x_2 + r_2$

Layer 1 is known as fuzzification layer. It consists of defined membership functions of the crisp input variables. Gaussian or bell shaped functions can be used at this layer. Using bell shape MF as an example, the output of the i^{th}node of layer 1 is given below:

$$O_i^1 = \mu_{A_i}(x)$$

$$\mu_{A_i}(x) = \frac{1}{1 + [\left(\frac{x-c_i}{a_i}\right)^2]^{b_i}}$$

or

$$\mu_{A_i}(x) = exp\{-(\frac{x-c_i}{a_i})^2\}$$

Where *x* is the input to node i, A_i is the linguistic label associate with the node function. O_i^1 is the degree of member function of A_i. As the values of parameter set $\{a_i, b_i, c_i\}$ changes the value and shape of the bell function changes too.

Layer 2 nodes are the firing strength of the product of the membership grades. The output of this layer is weights, W an outcome of AND rule operator applied to layer 1 MFs nodes. All the nodes in this layer are circular, labeled Π, T-norm operator which performs AND function

$w_1 = \mu A_1(x) + \mu B_1(y)$, i=1,2

Layer 3, sometimes known as the 'normalized firing strengths' or 'average node' layer. Each node of this layers calculates the ratio of the i^{th} weight to the sum of other weights from layer 2 nodes.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2 + w_3 + w_4}$$

Layer 4 which is also called the defuzzification layer or consequent nodes layer provides output values from the product of the i^{th} inference rules and the weighted output from Layer 3. Where (p, q, r) are consequent parameters.

$O_{4,i} = \overline{w}_i f_i = \overline{w}_i \,(p_i x_i + q_i x_i + r_i)$

Layer 5 labeled as Σ is called the output layer. This layer consists of a single node that computes the summation of signals from preceding layer 4. This layer also transforms the fuzzy-set outputs into a crisp value.

$$O_1^5 = overall\ output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

RESEARCH METHODOLOGY

i. Propagation Environment: Drive test was conducted on the 3rd floor of a 5-story office buildings in Ilupeju Lagos, Nigeria. Test drive was conducted in a 15-meter closed corridor general office with furniture and other office equipment that may impact the propagation of wireless signal in the path way between the transmitter and receiver.

ii. Signal Measurement: Wireless signal strength measurements were taken using Cisco Aironet 3602 Access Point (AP) that is IEEE 802.11a, b, g and n compliant. The AP has the capability to operates on both 2.4 GHz and 5.0 GHZ radio spectrum. For the purpose of this experiment 2.4 GHZ radio was used with a bandwidth throughput of 11 Mbps. These measurements were carried out twice per day (off-peak and peak) for a period of 6 months with HP Elite book 840 laptop with wireless adapter. RSSI measurements were taken at regular increments of distance of 1 meter from the transmitter (AP). The observed RSSI mean values and SNR data were recorded in a database for further processing.

iii. Statistical Analysis: The data collected was subjected to statistical analysis; Minimum Mean Square Error (MMSE) was used to estimate path-loss exponent n value, which was later used in computing RSSI derived values from the Chipcon model. Comparison and evaluation of ANFIS, Observed data (drive test), and Chipcon RSSI models was later done using RMSE, and Chi-Square goodness of fit test.

DATA ANALYSIS

The first part of the data analysis deals with predicting the received signals strength using Chipcon RSSI models, this will later be compared with ANFIS prediction model. The same RSSI observed data collected over six months was used for both Chipcon and ANFIS models analysis. Mean values of the data was evaluated by finding the average values of the daily peak and off-peak data for the six months' period.

<u>Overview of the Empirical Model</u>

The Chipcon RSSI model was derived from Log-normal path-loss model, and it's one of the suitable empirical models for indoor wireless propagation modeling for RSSI.

Chipcon RSSI = $-10n \,\boldsymbol{log_n} d + A$ **(1)**

where RSSI = the signal power at the receiver, n= Path loss exponent, d = distance between the transmitter and Receiver, A = the received power at one-meter distance. With linear regression, pathloss exponent n can be evaluated by finding Minimum Mean Square Error (MMSE) of the observed pathloss and the calculated pathloss [6].

$J(n) = \sum_{i=1}^{k}\left[\left(P_L - \overline{P_L}\right)\right]^2$ **(2)**

where, P_L is observed value and $\overline{P_L}$ is the calculated value from equation:

$J(n)=$

$$\sum_{i=1}^{k}\left[P_L - \overline{P_L}(d_0) - 10n\,log\left(\frac{d}{d_0}\right)\right]^2$$

Differentiating with respect to n:

$$\frac{\delta\, J(n)}{\delta\,(n)} = -20n\,log\left(\frac{d}{d_0}\right)\sum_{i=1}^{k}\left[P_L - \overline{P_L}(d_0) - 10n\,log\left(\frac{d}{d_0}\right)\right]$$

Taking $\frac{\delta\, J(n)}{\delta(n)}$=0, and dividing through by $-20n\,log\left(\frac{d}{d_0}\right)$:

$$\sum_{i=1}^{k}[P_L - \overline{P_L}(d_0)] - \sum_{i=1}^{k}\left[10n\,log\left(\frac{d}{d_0}\right)\right] = 0$$

$$n = \frac{\sum_{i=1}^{k}[P_L - \overline{P_L}(d_0)]}{\sum_{i=1}^{k}\left[10\,log\left(\frac{d}{d_0}\right)\right]} \quad \textbf{(3)}$$

Computing with Matlab, the pathloss exponent n value is **2.96.**

Putting n=2.96 into Equation (1)

Chipcon RSSI = -10n $\log_n$d + A

and distance d is incremented from 1 to 15 meter, Empirical RSSI for each distance is calculated.

Overview of the ANFIS Model

For the five layered ANFIS model, Matlab's Neuro-Fuzzy designer was deployed, about 67 % of the dataset was used to train the ANFIS model, error tolerance of 0.1 and 40 epochs was also set. The ANFIS structure comprises of a two input and one output Takagi and Sugeno system with generalized Gaussian membership function MF, defined as:

$$\mu A_i(x) = exp\left[\left(\frac{-(x-ci)}{a_i}\right)^2\right]$$

where a_i, and c_i are the non- linear premise parameter set.

Changing the values of premise parameters will change the shape of the membership function. The architecture is such that, the two inputs represent the measured distance and Signal to Noise Ratio values, while the predicted RSSI values is represented at the output of the ANFIS. The learning algorithm implemented for training the network is forward pass and backward pass hybrid.

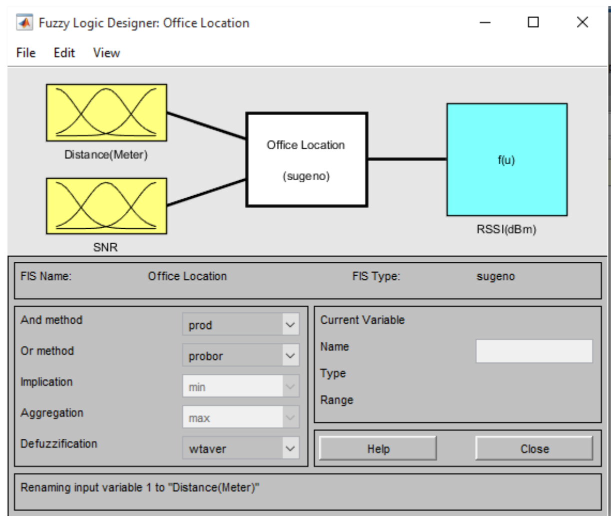

Figure 2: The Fuzzy Logic Designer.

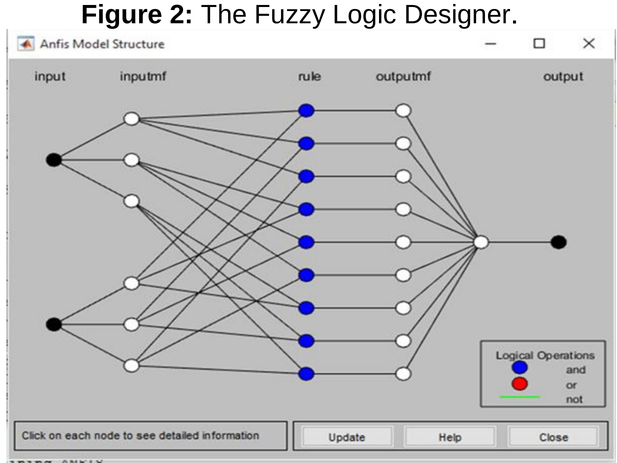

Figure 3: The ANFIS Model Structure.

The ANFIS rule used is also a 3^2 =9 rules with linguistic variable as 'VERY NEAR 'NEAR', 'FAR' respectively for input 1 and 'Best', 'Better' and 'Good' for input 2. After applying the training and testing datasets, each RSSI output value is computed from the rule viewer by moving the distance and SNR slides to the corresponding input values. For instance, to obtain RSSI value for distance 1-meter, on the rule viewer set the distance slide to 1 and the corresponding SNR to 42.32, the RSSI output value would be read as -48.4 (dBm).

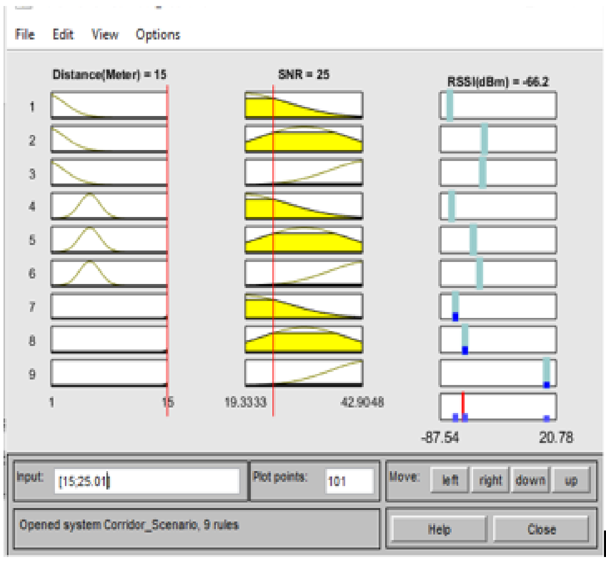

Figure 4: ANFIS Rule Viewer.

RESULTS

Comparison of Models

From Table 1 below, it can be seen that ANFIS outputs are more suitable and closer to the observed data than Chipcon empirical prediction model. Comparing statistical performances of the three models Table 2 depicts standard deviation, RMSE and Chi-square goodness-of- fit test values for the models. Using 3rd order polynomial curve fittings, the RMSE values for Observed, Chipcon and ANFIS models are 2.822, 3.374 and 0.353 respectively while the (R-square) values are 0.8463, 0.9034 and 0.9987, respectively.

In conclusion, the paper has been able to present the fact that ANFIS based RSSI prediction can yield satisfactory results in terms of model accuracy for indoor WLAN (2.4GHZ) propagation environments. Furthermore, the ANFIS model appears to strike the perfect balance between simplicity and correctness. It is considerably more accurate than Empirical (Chipcon) model, while requiring only small amounts of site information as input. This also suggest the possibility of using simpler, less complex models to perform planning and designing of wireless networks.

Table 1: Model Comparison

	Comparison of Models			
Meter	SNR	RSSI Observed	RSSI Empirical	RSSI ANFIS
1	42.32	-49.42	-49.42	-48.4
2	38.36	-52.13	-58.33	-49.6
3	35.37	-53.75	-63.54	-52.1
4	33.91	-56.63	-67.24	-55.9
5	34.21	-57.35	-70.11	-57.4
6	35.71	-56.34	-72.45	-56.7
7	32.70	-58.80	-74.43	-59.2
8	26.01	-64.00	-76.15	-65.2
9	22.46	-67.77	-77.67	-68.4
10	22.55	-68.30	-79.02	-68.1
11	22.64	-68.31	-80.25	-67.3
12	25.96	-64.84	-81.36	-61.9
13	20.93	-69.32	-82.39	-68.2
14	20.68	-70.23	-83.35	-69.7
15	25.11	-65.77	-84.23	-66.1

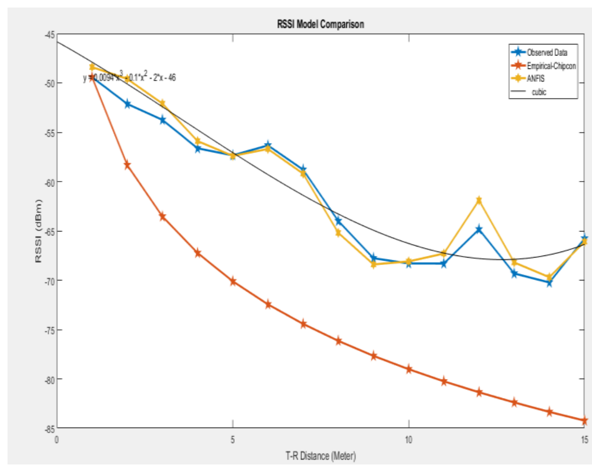

Figure 5: RSSI Model Comparison.

Table 2: Model Performance Analysis.

	Statistical Performance Analysis of Models		
	Standard deviation	RMSE	R-square
RSSI(Observed)	6.936	2.822	0.8463
RSSI (Chipcon Empirical)	10.05	3.374	0.9034
RSSI (ANFIS)	7.297	0.353	0.9987

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