

# Statistical Data Performance Modelling and Prediction of Indoor Wireless LAN Signal Strength

<sup>1</sup>Shoewu, O.O., <sup>2</sup>Akinyemi, L.A., <sup>3</sup>Basorun, O.O

1. Department of Electronic and Computer Engineering, Lagos State University, Epe Campus, Epe, Lagos, Nigeria
2. Department of Industrial Maintenance Engineering, School of Industrial and Manufacturing Engineering, Yaba College of Technology, Nigeria

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## Abstract

This paper describes a study on statistical data performance of indoor wireless signal strength prediction using Adaptive Neuro-fuzzy system. Measurements of signal strength was conducted on a third floor of a five storey office building situated in Ilupeju area of Lagos State, Nigeria. 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 measurement 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. have shortcomings and are 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*

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## 1. INTRODUCTION

The high rise in demand for bandwidth has necessitated the need for multimedia requirement 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, using statistical data. The 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 research 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 to the data collected from the observed data and an Empirical model.

This paper is organized as shown in the foregoing. In section 2, related works and radio channel models were discussed. Section 3 describes ANFIS structure and statistical analysis required to compare the model with other existing models. Section 4 describes the methodology employed in this study. In section 5, Data Presentation and Analysis were presented. While section focused on result analysis. Finally, the conclusions drawn from this study are summarized in section 6.

## 2. 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 O.S, 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 developed a neuron network system to predict RSSI in a particular indoor environment, data from three different access points was used to train the system. The result was compared with 3-D Ray Tracing deterministic model and a neuron network prediction model was developed.

This research work 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. Next sections of this chapter review radio wave propagation and different models that are applicable to indoor wireless propagation. Although many of the techniques developed to characterize the outdoor propagation environment can readily apply within buildings [9], there are still a bit of odds as the indoor environment geometry is more complex and there may not be one solution fits all. In other 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. The latter parts of the chapter will introduce Artificial Intelligence techniques focusing on adaptive neuro-fuzzy inference systems [21]. 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]. Advantage offered by artificial intelligence are flexibility to be used to model different environment and high-speed processing capability.

## 3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

RSSI prediction in indoor RF propagation environment is usually perceive as complex and time consuming venture. Numerous types of prediction methodology have been employed in developing different ways of characterizing the propagation channels. However, these models

hardly adapt to divergent indoor RF environments. 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 and proposed what is today 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 its 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.

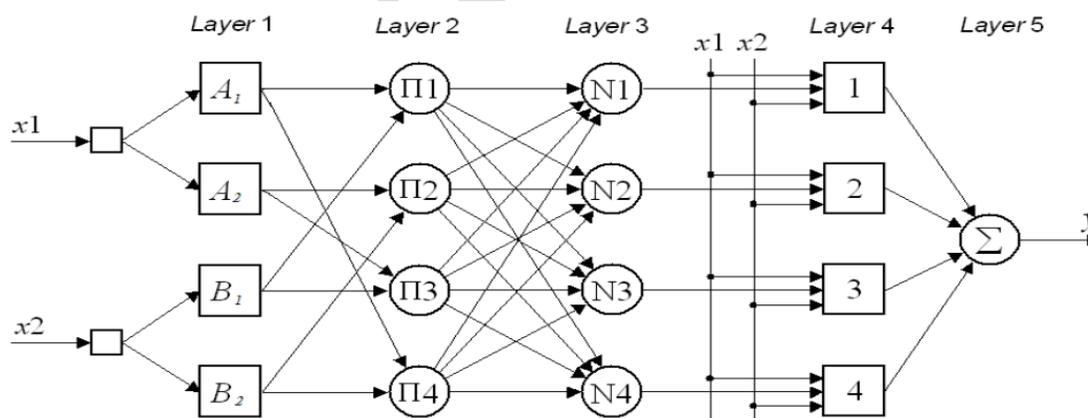


Fig 1: Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993)

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  $f_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2: If  $x_1$  is  $A_2$  and  $x_2$  is  $B_2$ , then  $f_2 = p_2x_1 + q_2x_2 + r_2$

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

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

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

or

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

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  $\Pi$ , T-norm operator which performs AND function

$$w_i = \mu_{A_1}(x) + \mu_{B_1}(y), \quad i=1,2$$

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.

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

Layer 5 labeled as  $\Sigma$  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.

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

#### 4. RESEARCH METHODOLOGY

**i. Propagation Environment:** Drive test was conducted on the 3rd floor of a 5-storey 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 measurement 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.

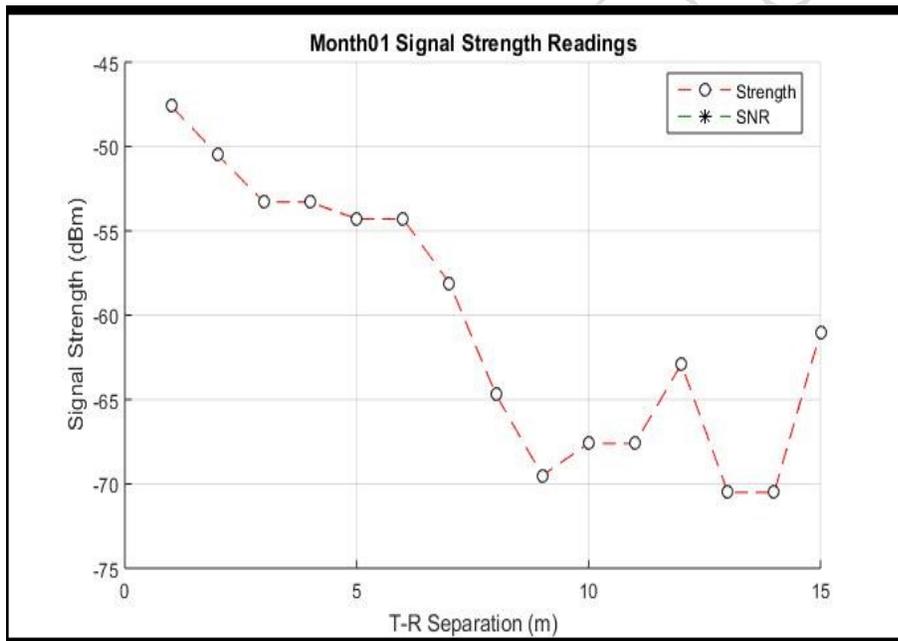


Fig 4.4a: First Month Signal Strength Readings

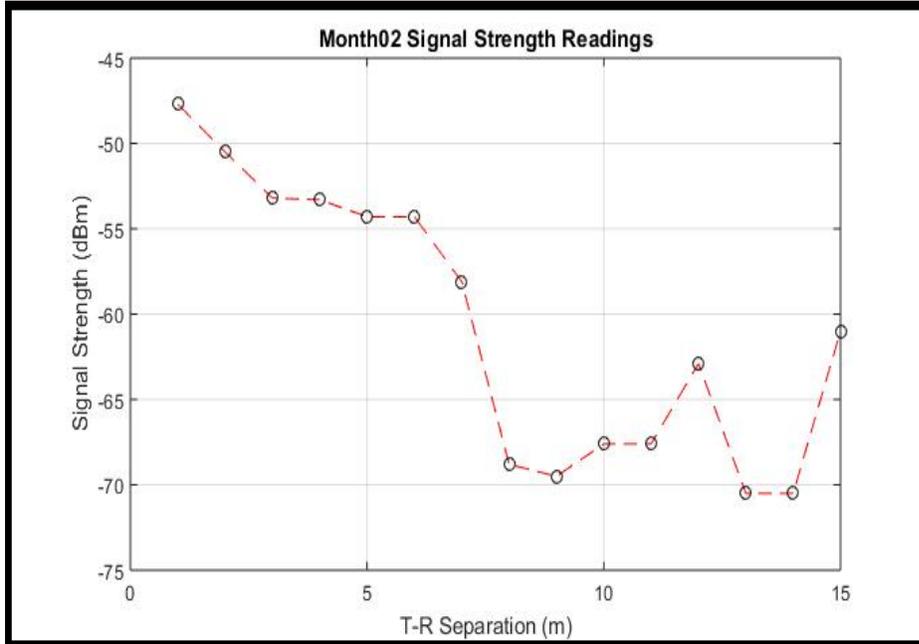


Fig 4.4b: Second Month Signal Strength Readings

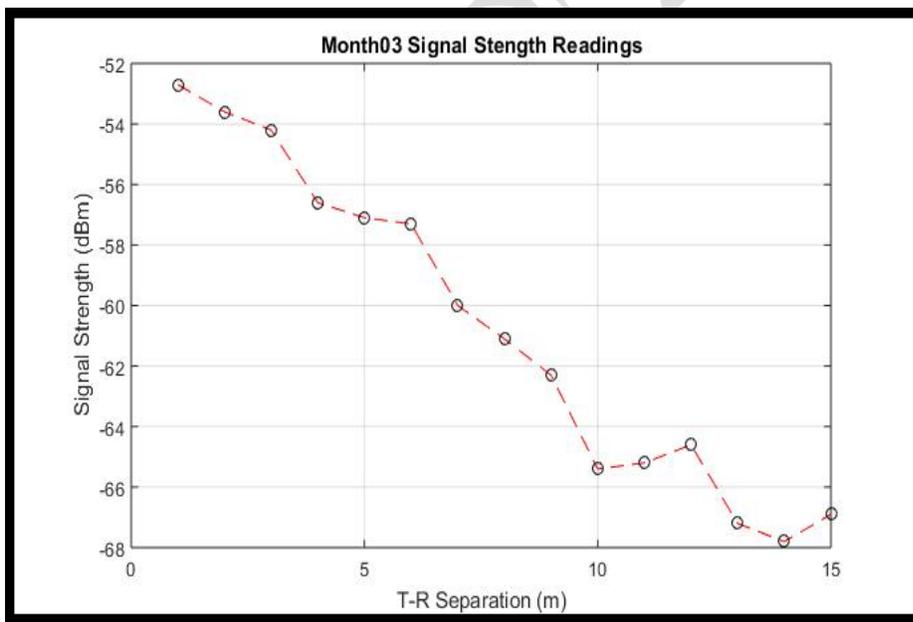


Fig 4.4c: Third Month Signal Strength Readings

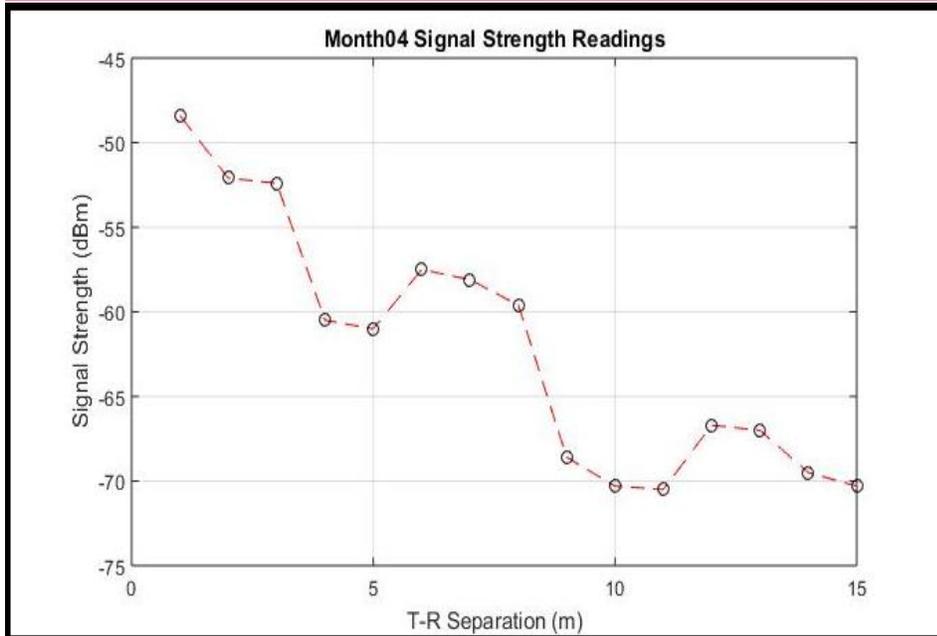


Fig 4.4d: Fourth Month Signal Strength Readings

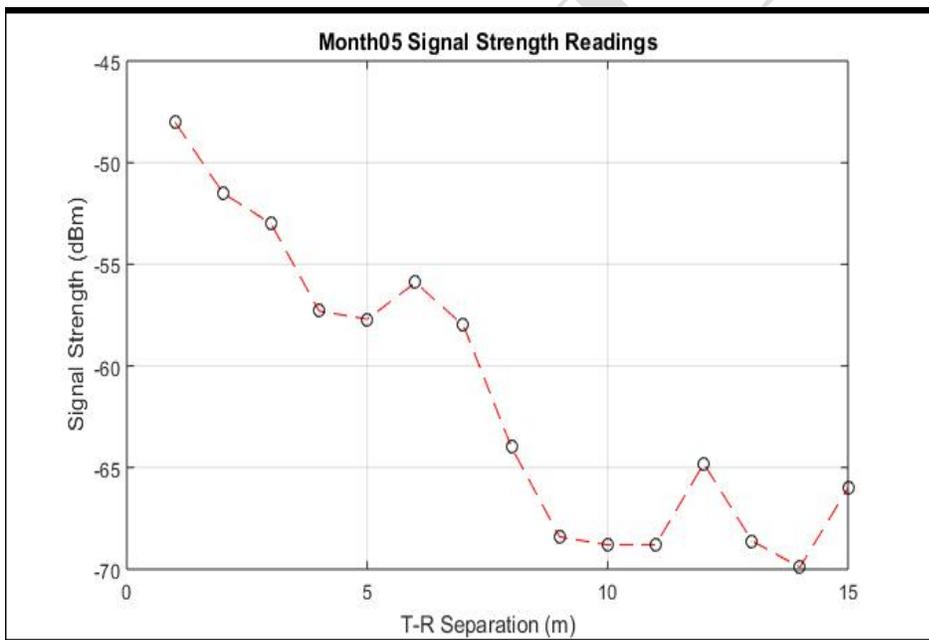


Fig 4.4e: Fifth Month Signal Strength Readings

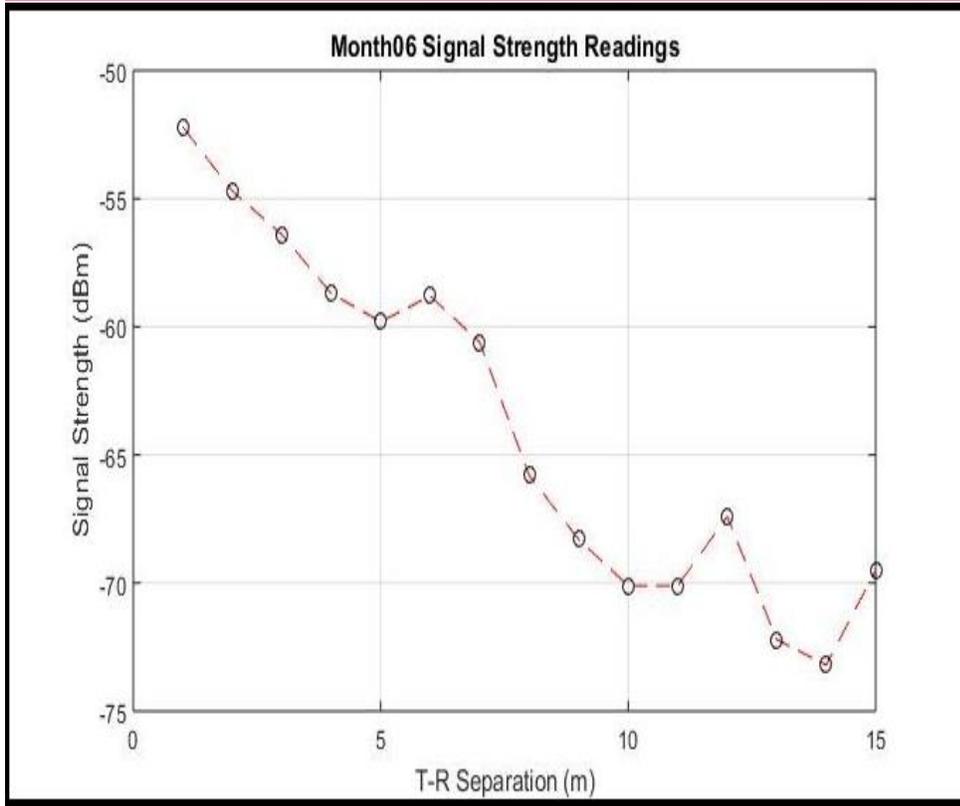


Fig 4.4f: Sixth Month Signal Strength Readings

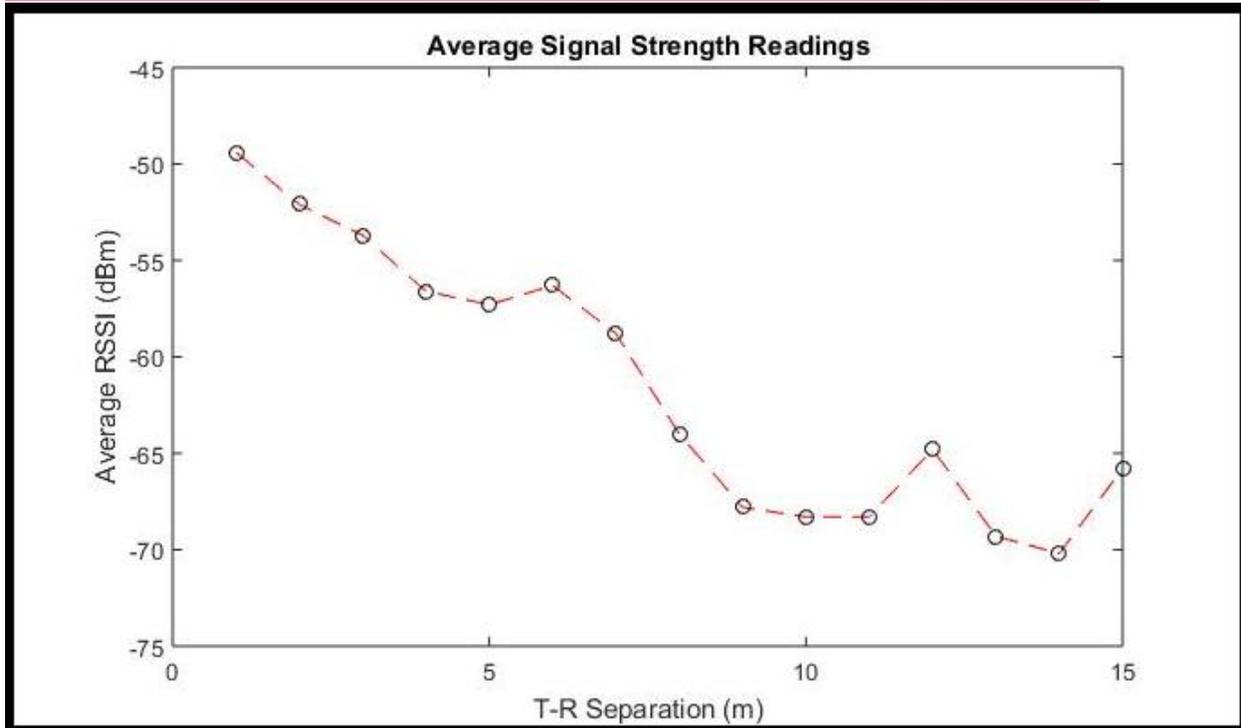


Fig 4.5: Mean RSSI Readings for Scenario 1

2. Calculate curve fitting using least square method:

MATLAB curve fitting tool which is a graphical user interface tool is employed to explore data and fits the observed data to the curve. Least square method technique is described as an algebraic procedure for fitting linear equations to data. A linear fit is calculated using least squares method, and fig. 4.6 shows the linear curve fittings for the observed data collected. The result collected for scenario1 are also presented.

Linear model Poly1:

$$f(x) = p1 * x + p2 \dots\dots\dots(4.1)$$

$$p1 = -1.429 (-1.794, -1.064)$$

$$p2 = -50.08 (-53.4, -46.76)$$

RMSE: 2.827

The goodness of fit  $R^2$ :0.8463

The goodness of fit for the observed data is 0.8463, this confirms that it can be applied in a similar radio characteristics environment.

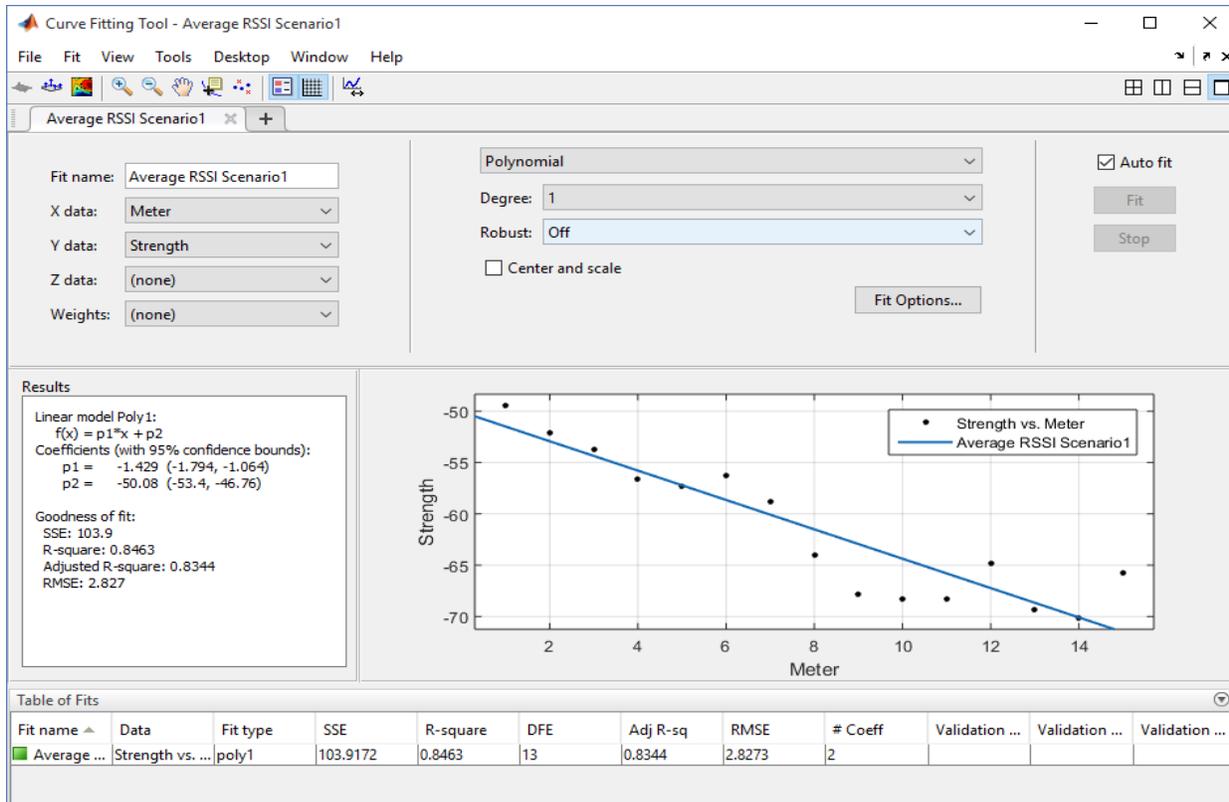


Fig 4.6: Least Square Method curve fittings for scenario1

### 3. Evaluate path loss exponent n, in Log-distance Path Loss Model

Least Square method curve fitting gives a linear equation of the form in (4.1), using the Minimum Mean Square Error (MMSE) estimate for the path loss exponent n can be found by using the formula below to evaluate Log-distance Path Loss Model (2.3). [6]

$$J(n) = \sum_{i=1}^k [(P_L - \bar{P}_L)]^2 \quad (4.1)$$

Where,  $P_L$  is measured value and  $\bar{P}_L$  is the calculated value from equation (2.3)

$$J(n) = \sum_{i=1}^k \left[ P_L - \bar{P}_L(d_0) - 10n \log\left(\frac{d}{d_0}\right) \right]^2 \quad (4.2)$$

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  $-20n \log\left(\frac{d}{d_0}\right)$

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

$$n = \frac{\sum_{i=1}^k [P_L - \overline{P}_L(d_0)]}{\sum_{i=1}^k \left[ 10 \log\left(\frac{d}{d_0}\right) \right]} \quad (4.3)$$

Computing equation (4.3) with Matlab (See Appendix 1 for code), the path loss exponent is 2.96 for Scenario1 of the test conducted. From section 3.1.5 received Signal Strength values can be predicted using Chipcon model

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

RSSI = the signal power at the receiver, n= Pathloss exponent from the curve fitting, d = Distance between the transmitter and Receiver, A = the received power at one-meter distance. For this scenario, the distance d = 1-meter step, Pathloss exponent n = 2.96, A = -49.4 dBm.

#### 4.1.2 Analysis of Result in Scenario 2: Open office room

Figure 4.7 gives the average signal strength (in dBm) versus T-R (Transmitter-Receiver) separation (in meters) for the AP. The experiment was conducted in an open office area on 3<sup>rd</sup> floor at Deloitte Lagos office. As seen from Figure 4.3 signal strength reduces as one goes further away from the access point, although, there are some exceptions which may be due to line of sight measurements or multipath effects The total distance of measurement for the experiment is 10m across the office area with one-meter step distance interval.

The pathloss n, for the second scenario can also be evaluated using equation (4.3)

i.e

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

Computing with Matlab, the pathloss exponent n is 3.64. From section 3.1.5 received Signal Strength values can be predicted using Chipcon model  $RSSI = -10n \log_n d + A$

RSSI = the signal power at the receiver, n= Pathloss exponent from the curve fitting, d = Distance between the transmitter and Receiver, A = the received power at one-meter distance.

For this scenario, the distance d = 1-meter step, Pathloss exponent n = 3.64, A = -56.98 dBm.

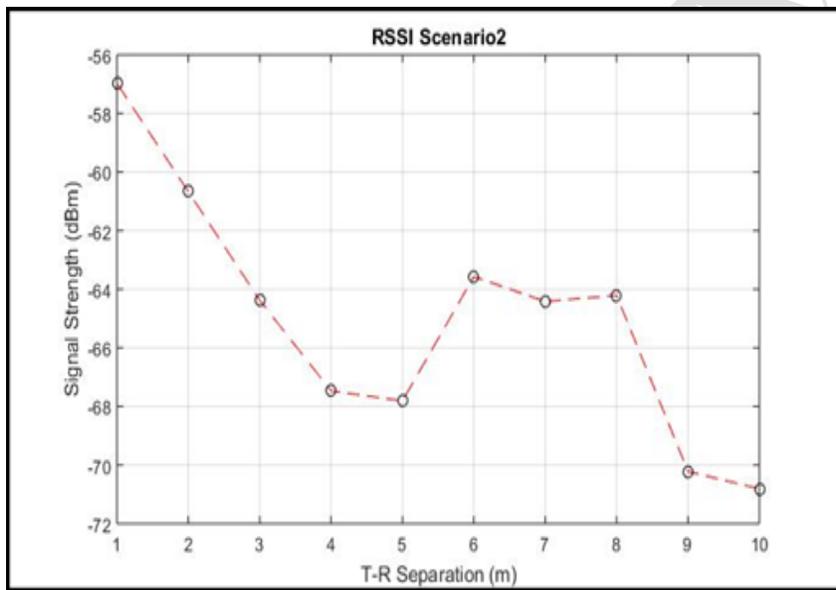


Fig 4.7: Mean Signal Strength curve for scenario2

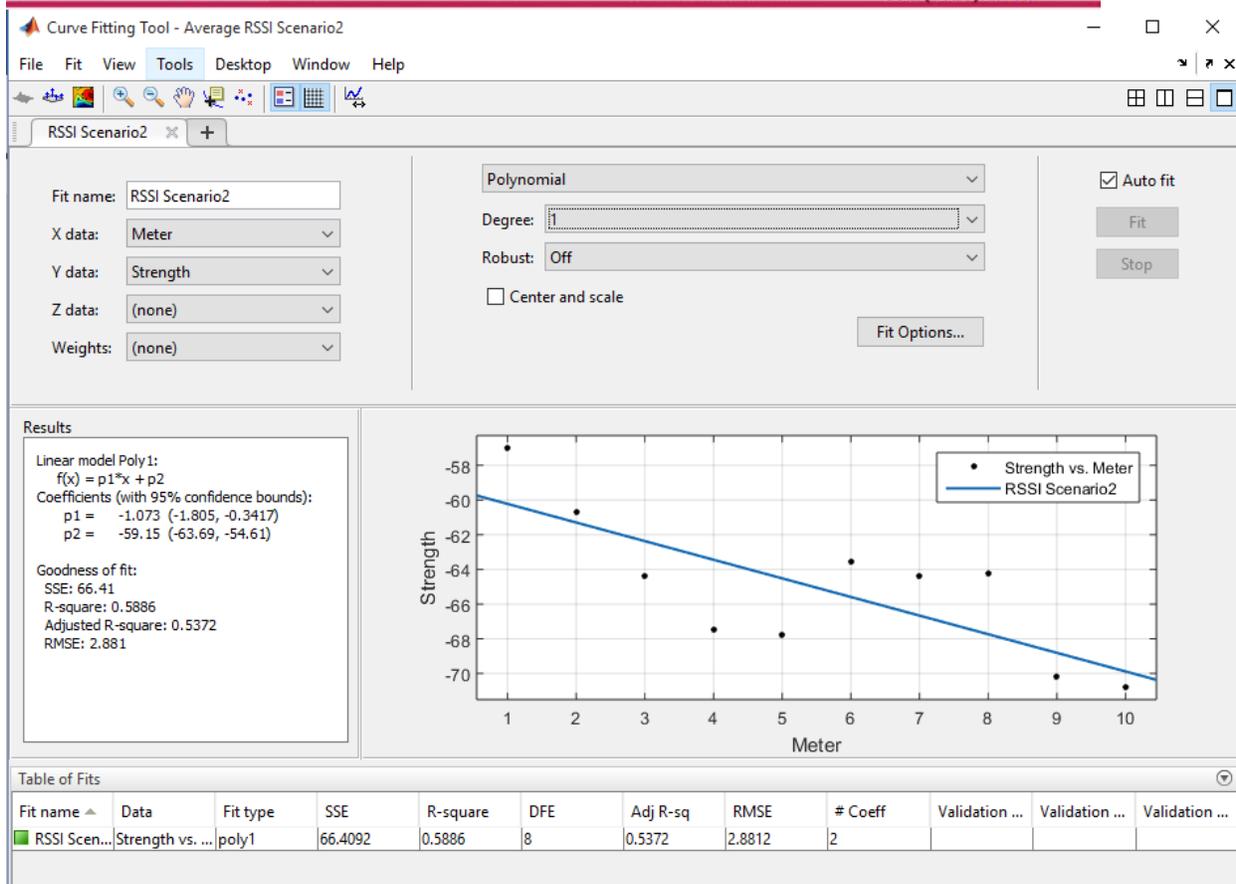


Fig 4.8: Least Square Method curve fittings for scenario2

Linear model Poly1:

$$f(x) = p1 * x + p2 \dots\dots\dots(4.2)$$

$$p1 = -1.073 (-1.805, -0.3417)$$

$$p2 = -59.15 (-63.69, -54.61)$$

RMSE: 2.881

The goodness of fit  $R^2$ :0.5886

The goodness of fit for the observed data is 0.5886, this confirms that it can be applied in a similar radio characteristics environment

## 4.2 ANFIS Model Analysis

Accurately modelling and appraising indoor radio signal propagation in a wireless local area network (WLAN) is challenging, but importantly is the task of determining ideal placement of access point (AP) locations to provide 100% coverage with signal strength above a least threshold value over its target areas. For effective design of WLAN, network designers and engineers rely on conducting site survey. These surveys involve collecting signal strength data over a period of time. But just like any other endeavor collection of data has its own shortcomings, some parts of the target area might be inaccessible during the active survey. Changes in environment may affect quality of measurements and cause variations in collected observed data. It is also noted that site surveying is a very time consuming and labour intensive process.

These shortcomings informed the need for a more robust signal strength prediction tools that also be used to predict signal strength in similar WLAN propagation environment.

ANFIS model provided a robust prediction capability for indoor radio propagation. In this study an ANFIS Model is described and a neuro fuzzy system is trained on the basis of training data set which are subset of processed data. The data was collected over 6 months' period, with 67 % used to train the ANFIS model. After Defining the model, it is run with various FIs Algorithm and error tolerance of 0.1 and 40 epochs. The ANFIS is modeled using anfisedit and performance analysis parameters RMSE, goodness fit is analyzed using various curve fitting model and these results are compared with the observed data and Chipcon empirical model.

### 4.2.1 Structure of ANFIS

The architecture of Neuro Fuzzy used in this study is ANFIS. This study applies a five layered ANFIS Model and the learning algorithm for training the network is hybridization of forward pass and backward pass. The ANFIS is a two input and one output Takagi and Sugeno system. The two inputs are step distance in Meter and Signal to Noise ratio (SNR) values with 3 membership function, and predicted RSSI values as the output.

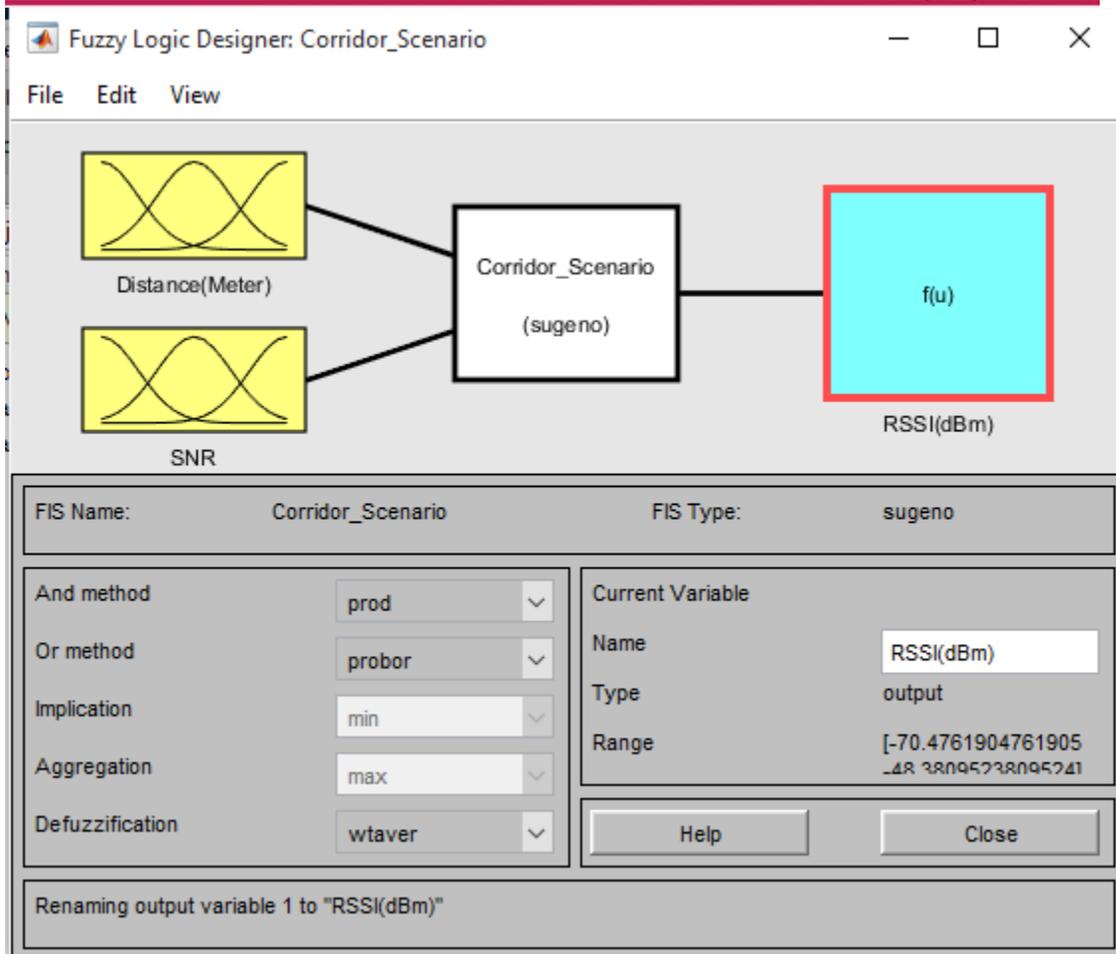


Fig 4.9a: Neuro-Fuzzy design showing input and output

Layer 1 is responsible for mapping of the input variable relatively to each membership functions. In this study, ANFIS will be running structures influence by membership functions of form (3,-1) which represents various fuzzy variable from low to high with input 1 as transmitter receiver distance (Meters) and input 2 as SNR values. The output is a single RSSI whose degree of membership is Linear. Besides this, the membership function “*gauss*” will be use in this study.

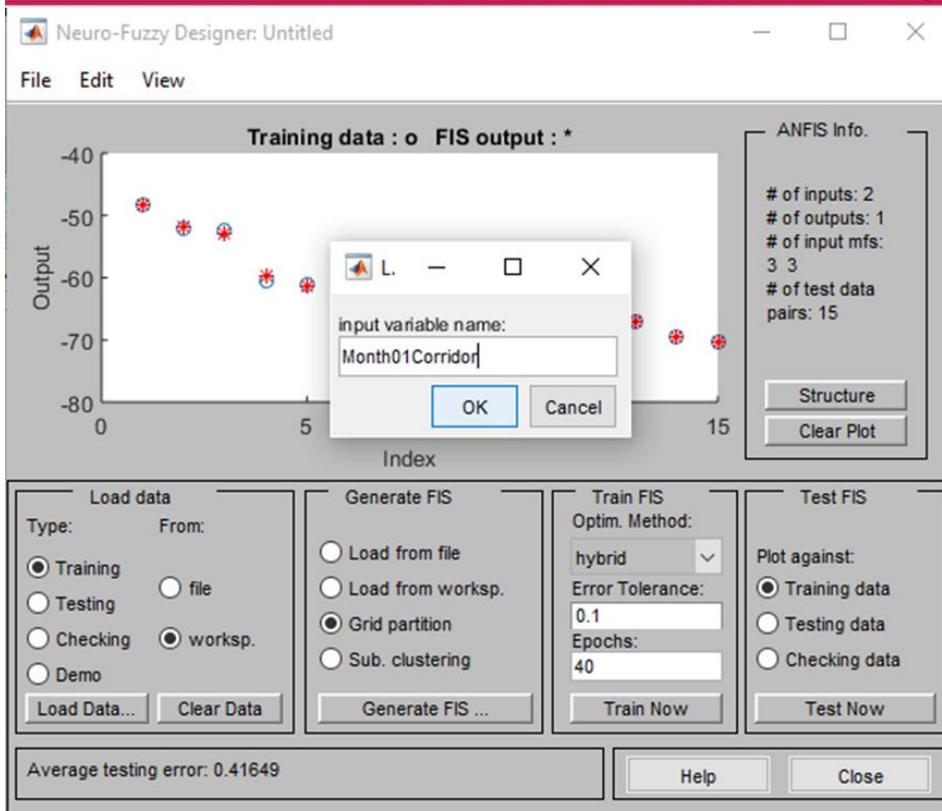


Fig 4.9b: Neuro-Fuzzy designer

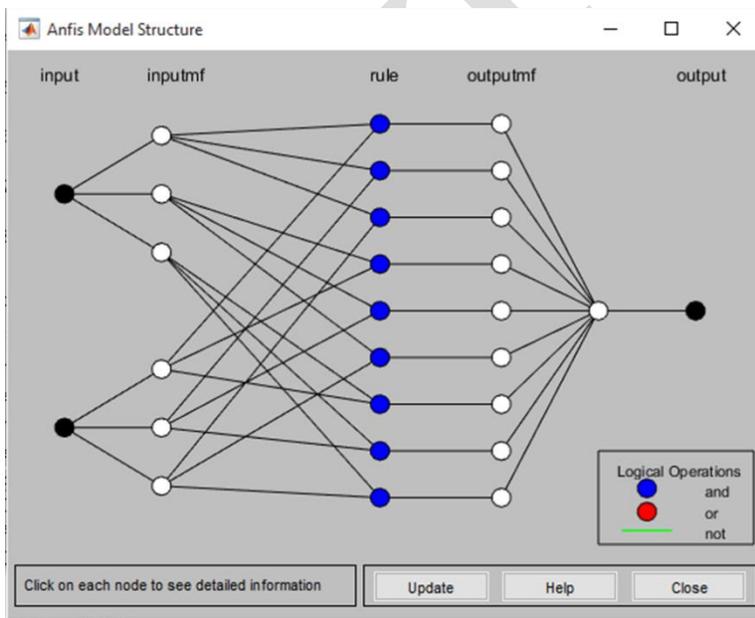


Fig 4.10: General Structure of ANFIS used in this Research

#### 4.2.2 Hypothesis of the Model used

ANFIS is more complex than the fuzzy inference systems, and is applicable for specific type of fuzzy inference system options. Specifically, it only supports Sugeno-type systems, and must have the following properties:

- Sugeno-Type systems should be of first order.
- There should be a single output, obtained using weighted average defuzzification.

All output membership functions are linear in this study

- In this model different rules cannot share the same output membership function,
- All fuzzy if-then rules have unity weight.

#### 4.2.3 Membership Function used

**Generalized Gaussian membership function:** Also called simply gauss MF, is defined as:

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

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

Changing the values of a, b, c will change the shape parameters of the membership function.

One input set is used to train the ANFIS and there is one output. Figure 4.11 represent the membership function where the input represents the distance in meter and the output RSSI in the first scenario.

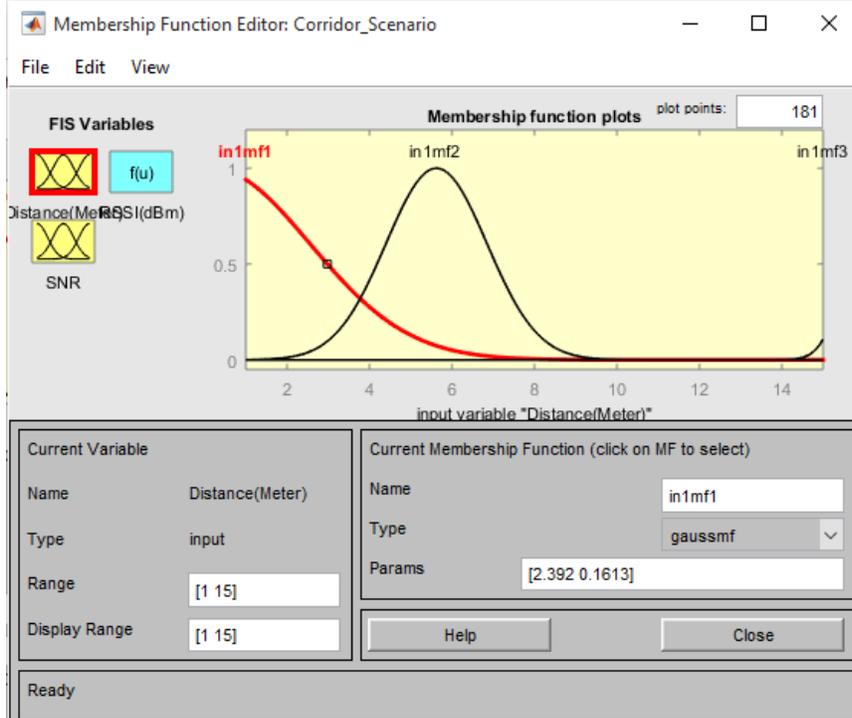


Fig.4.11: Membership function of input

#### 4.2.4 Hybridization of Learning Algorithms

This adaptive network is equivalent to Sugeno Fuzzy Model. A formula can be employed to find the values of non- linear premises parameters  $\{a, b, c\}$  and linear consequences parameter

$\{p_i, q_i, r_i\}$ , in the proposed research work Hybrid Learning Algorithms are used and the hybrid optimization method is a combination of Least-Squares and back propagation Gradient Descent method. One of the major reason for choosing Least-Squares is that in LSE, computational complexity is higher than others. However, for prescribed performance level, LSE is much faster

#### 4.2.5 ANFIS Setup

Using Matlab R2015a, a network is setup in ANFIS editor in mainly two stages - Sugeno ANFIS Setup and Training of ANFIS Model.

#### Sugeno ANFIS Setup Model

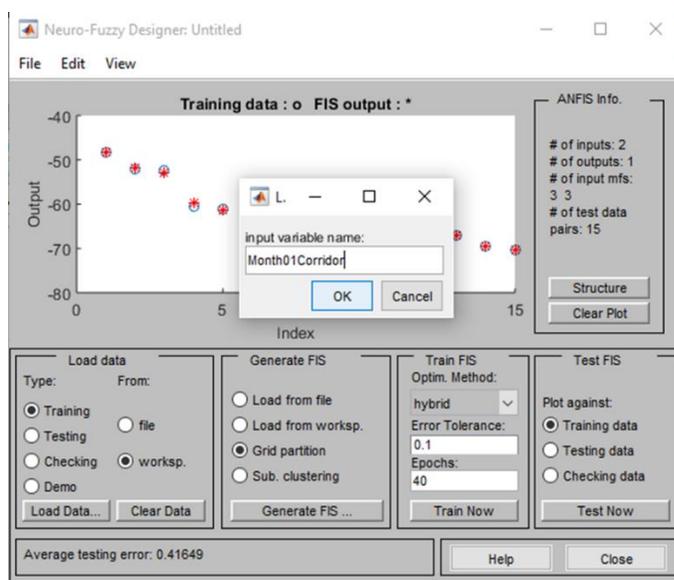
To design a network using ANFIS editor, first load input data from the workspace as in fig. 4.11 below. ANFIS editor separated as training and testing data set. Then generate FIS using Grid Partitioning method. Sample ANFIS information is:

*No. of input 2*

*No. of output 1*

*No. of input Mfs: 3*

Architecture of ANFIS model (2-3-1)



*Fig. 4.12: Loading of Training and Testing data*

## Training of ANFIS Model

Training of ANFIS model is done using hybrid optimization method with error tolerance level 0.1 for 40 epochs. Once the training is done, ANFIS model is always ready for the prediction. During this training, ANFIS will learn the whole pattern among the four months RSSI inputs and the fifth month data will be used to test the system.

## Means of Error Performance Evaluation

Like other models, various types of data analysis tools used for performance evaluation in the experiments are:

- Goodness of fit
- MSE or
- RMSE

### Testing of ANFIS Model

Testing of ANFIS model will enable us to fit the tested data with the training data. This compares the trained data to the tested data. As shown in figure 4.12, after 40 epochs average testing error for training data is observed is 0.41649 and RMSE is 1.61.

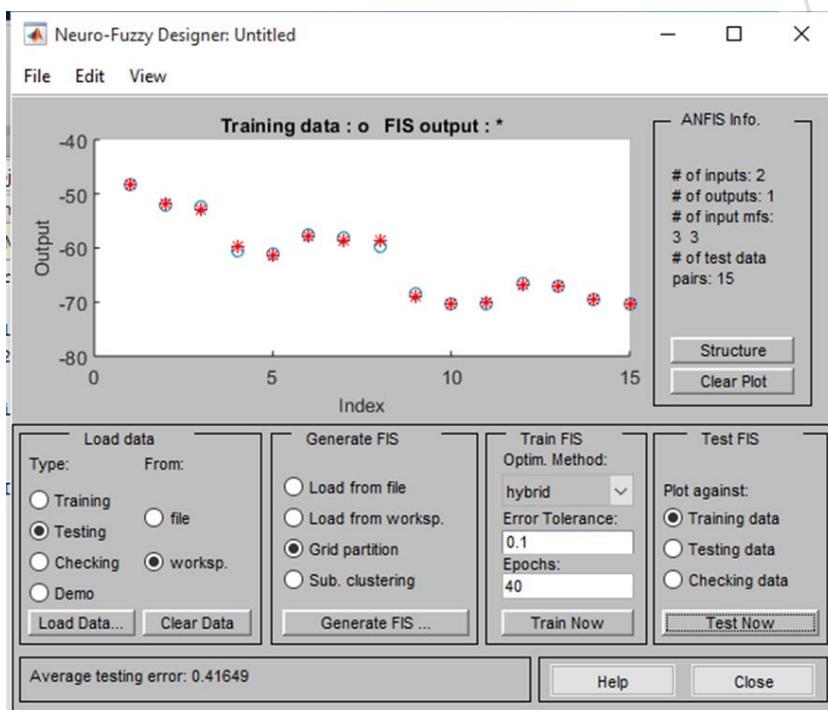


Fig:4.13: Training data vs Testing data set output

### 4.2.6 FIS Rules for Simulation

The ANFIS rule implemented is a  $3^2 = 9$  rules, the linguistic variable are 'VERY NEAR', 'NEAR', 'FAR' respectively for input 1 and 'Best', 'Better' and 'Good' for input 2. Layer 3 represent the number of rules generated. 9 rules were used for scenario1 and scenario2. The blue

spots in Fig 4.10, depict the rules-base on the ANFIS system. The predicted outputs are read from the rule viewer with inputs from 1 to 15.

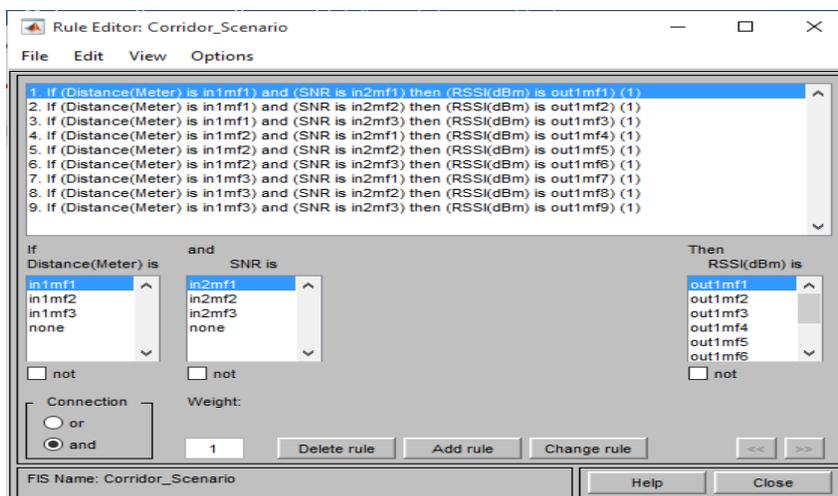


Fig:4.14: FIS rule editor

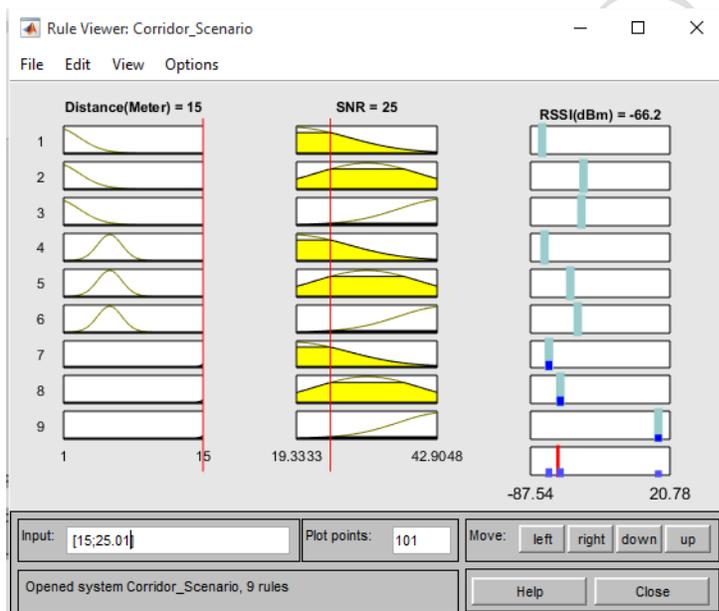


Fig:4.15a: FIS rule viewer sample inputs

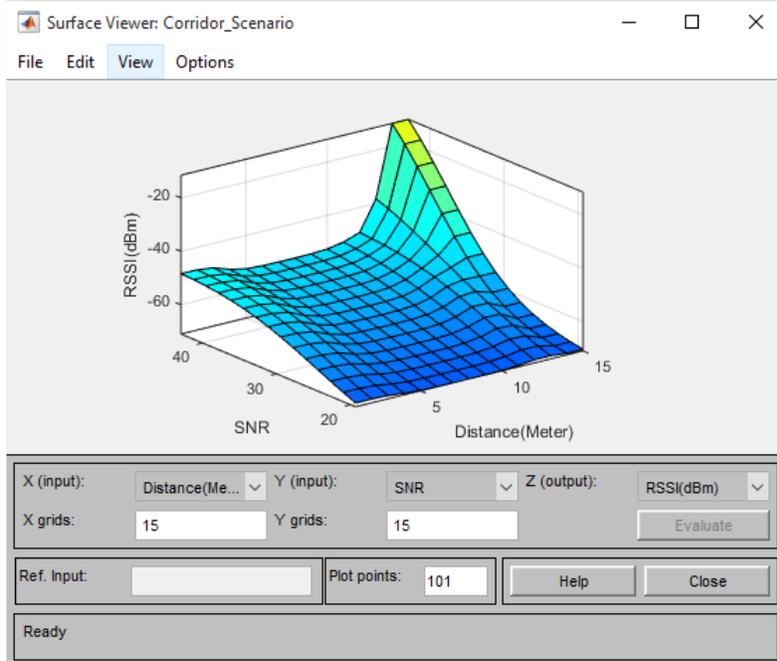


Fig.4.15b: 3D Surface viewer for Closed Corridor (Scenario1)

#### 4.2.6 Comparison with Similar Models

This section describes the statistical analysis for the two scenarios in the test building as described in previous sections and compares the results with similar models. The ANFIS prediction presented is using four-month mean readings to train the ANFIS system and one-month mean readings for testing. On trying out gbellmf, gauss2mf, trapmf and gaussmf, the gaussmf was best fitted for the prediction and it was implemented in both test scenarios. From the table it is clear that ANFIS outputs are more suitable and closer to the observed data than Chipcon empirical prediction model. Comparing statistical performances, table 14 & 16 depicts standard deviation, RMSE and Chi-square goodness-of-fit test values for all the models.

Table 5: RSSI models comparison for Closed Corridor (Scenario1)

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

Table 6: RSSI Model Statistical Performances

Statistical Performance Analysis Closed Corridor			
	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

For this experiment results, Linear, Log and polynomial function-model presented very good values for our study. In closed corridor scenario, Log fitting were conducted for RSSI (observed) values and polynomial regression for the ANFIS. Both models were compared. From Table 14, fitting degree (R-square) of log function was 0.8463 and that of the ANFIS was 0.9583. Both values show that the comparison is ideal fittings.

Recall from equation (3.1),  $RSSI = -10n \log_n d + A$

Inputting the path loss exponential value  $n=2.96$ , and  $A = -49.42$ .  $A$ , which is the RSSI is a combination of the frequency from transmitting terminal, the frequency of receiving terminal at the distance 1m and  $X\sigma$  which is a shadowing factor. The equation below presented a simplified log-normal Chipcon RSSI model obtained from the observed or experimental readings.

$$RSSI = -29.6 \log_n d - 49.42 \dots\dots (4.4)$$

On the other hand, using quadratic polynomial regression analysis for the ANFIS predicted values, from equation (4.3) the path loss exponent n, can be computed using MMSE Matlab function.

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

n = 2.95 and A= -48.4, therefore putting both values in equation (3.1) ANFIS RSSI model is

$$RSSI = 0.0094d^3 - 0.1d^2 - 2d - 46 \dots (4.5)$$

Inspecting both log-normal (observed) and ANFIS predicted models in equation 4.4 and 4.5, it can be seen clearly that ANFIS presented a close replica of the observed model.

Table 7: RSSI models comparison for office mode (Scenario2)

Comparison of Models				
Meter	SNR	RSSI Observed	RSSI Empirical	RSSI ANFIS
1	34.48	-56.98	-56.98	-58.20
2	30.33	-60.67	-60.21	-58.50
3	23.75	-64.38	-62.10	-66.60
4	20.04	-67.47	-63.44	-63.30
5	20.59	-67.81	-64.78	-62.10
6	26.69	-63.57	-65.33	-65.30
7	24.94	-64.42	-66.05	-63.60
8	27.48	-64.21	-66.67	-62.80
9	20.39	-70.22	-67.22	-68.50
10	18.58	-70.81	-67.71	-68.60

Table 8: RSSI Model Statistical Performances

Statistical Performance Analysis Office Scenario			
	Standard deviation	RMSE	R-square
RSSI(Observed)		1.879	0.8687
RSSI (Chipcon Empirical)		0.81	0.9967
RSSI (ANFIS)		2.011	0.8303

Applying same methodology for the closed office scenario, Log fitting were conducted for RSSI (observed) values and polynomial regression for the ANFIS. The models were then compared. Obtaining the pathloss exponent value from equation (3.1) both RSSI (observed) and RSSI (ANFIS) are  $n=3.64$  and  $n=3.60$  respectively. See Apendix..for screenshots of ANFIS system designed for the office mode.

For the RSSI Chipcon model path loss exponential value  $n=3.64$ , and  $A = -56.98$ .  $A$ , which is the RSSI is a combination of the frequency from transmitting terminal, the frequency of receiving terminal at the distance  $1m$  and  $X\sigma$  which is a shadowing factor. The equation below now shows the computed log-normal RSSI model obtained from the experimental readings.

$$RSSI = - 3.64 \log_n d - 56.98 \dots\dots (4.6)$$

Likewise, for the ANFIS analysis, using quadratic polynomial regression,

$$RSSI = 0.00074d^4 - 0.13d^3 + 2.1d^2 - 11d^1 - 47 \dots(4.7)$$

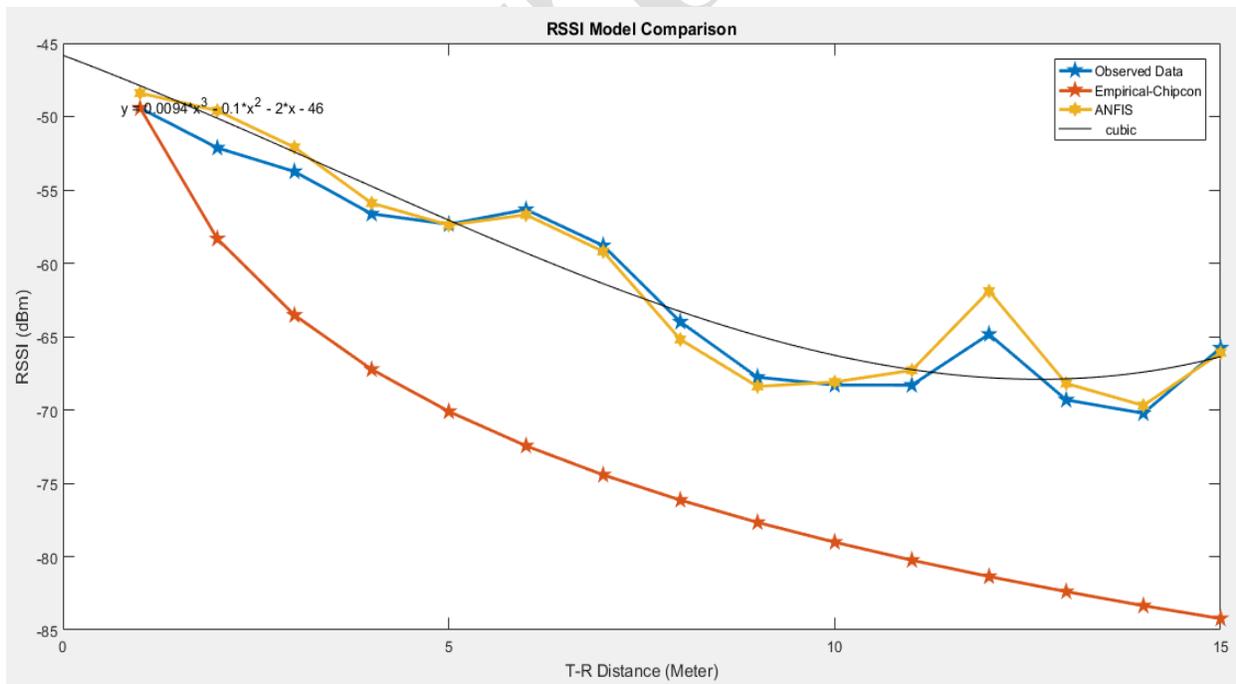


Fig.4.16a: Comparison of received signals in closed corridor (scenario1)

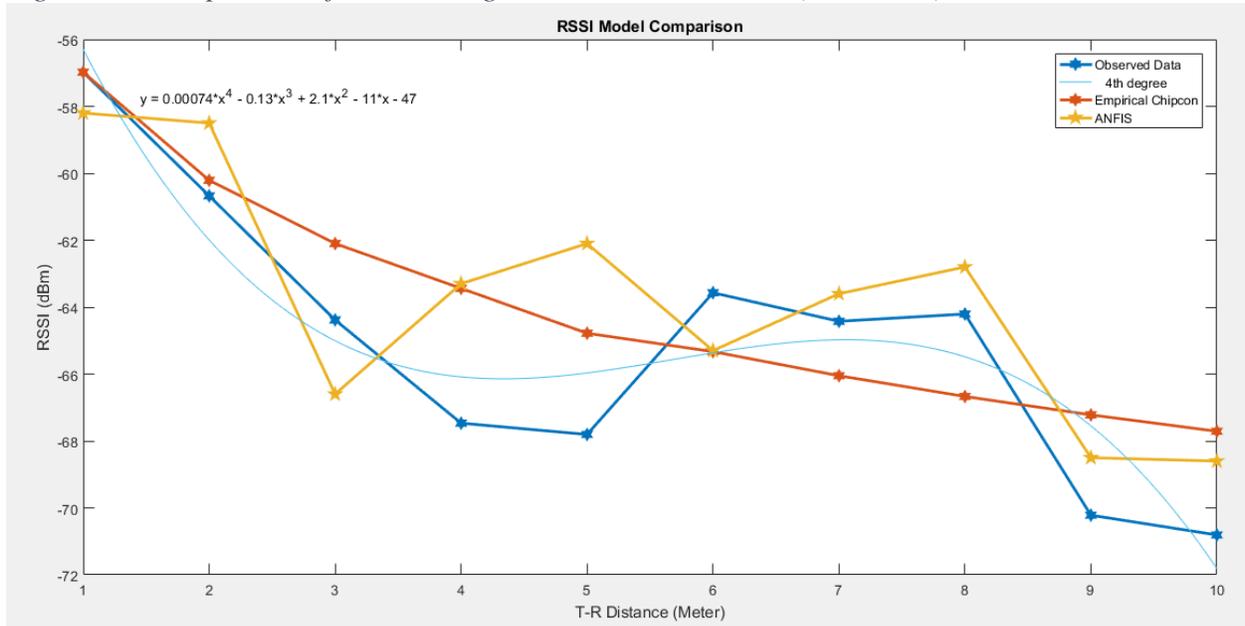


Fig.4.16b: Comparison of received signals in office (scenario2)

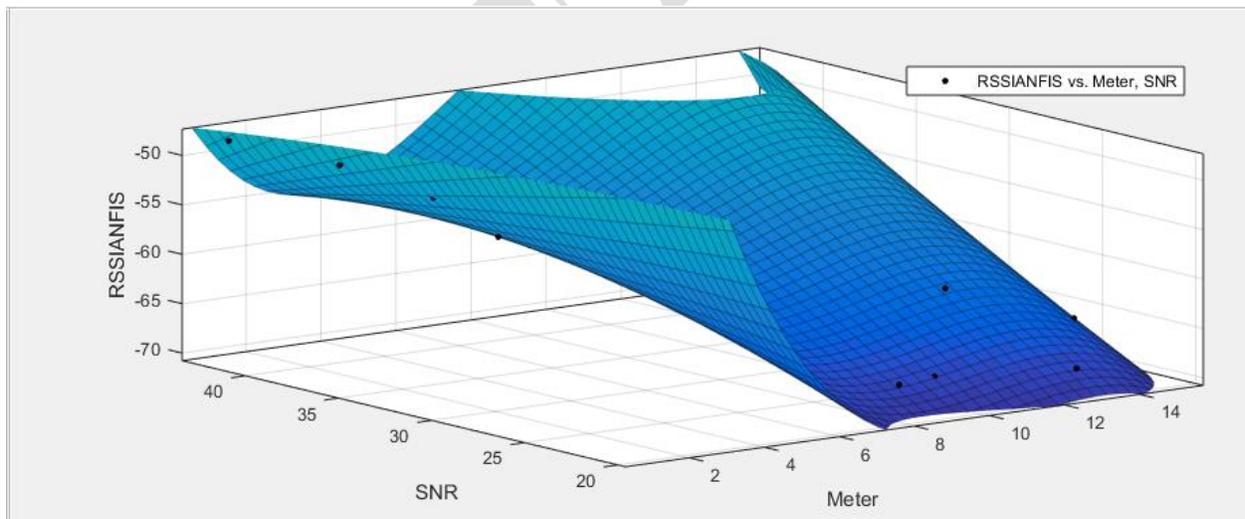


Fig.4.17: Curve fittings for ANFIS closed corridor (scenario1)

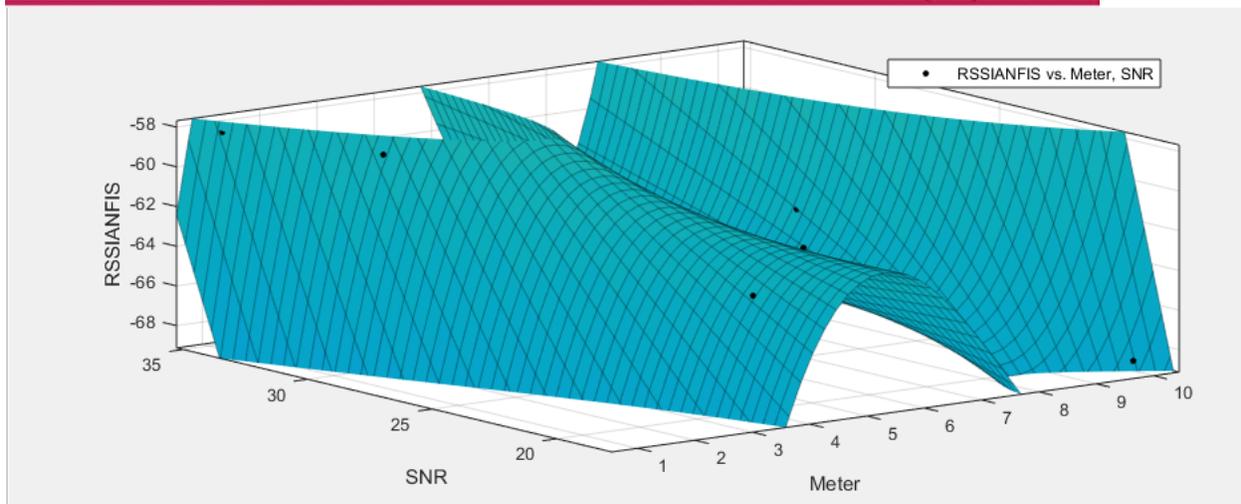


Fig.4.18: Curve fittings for ANFIS model data (Office scenario)

## Chapter 5

### Conclusion

From the analysis performed on measurements taken at the two test environments of Deloitte Ilupeju office, we can see that ANFIS based RSSI prediction can yield satisfactory results in terms of model accuracy for indoor WLAN (2.4 GHZ) propagation environments. Obtained ANFIS RSSI and path loss values agree with the values from collected observed data, and the standard deviation of the model errors are similar. Additionally, these results confirm the validity of using a cost effective, consumer WLAN card on laptops for measurement surveys intended for model analysis.

Furthermore, the ANFIS model appears to strike the perfect balance between simplicity and correctness. It is significantly more accurate than log-normal (Chipcon) model, while requiring only small amounts of additional site information as input. This also offers credibility to the possibility of using simpler, less sophisticated models to perform pre-deployment planning of wireless networks. The Adaptive Neuro Fuzzy Inference System prediction methodology was also verified as being an effective, accurate method for planning network infrastructure development. By performing initial site-survey and analysis on test areas in order to develop general model parameters for deployment simulation, this development methodology can drastically reduce the amount of time required to deploy a WLAN network, and therefore also reduce the cost associated with deployment. Using the ANFIS model deployment method there is potential faster deployment of WLAN networks at lower cost and better quality of service.

### References

- [1] T. S. Rappaport, *Wireless communications: principles and practice*: Publishing House of Electronics Industry, 2004.

- [2] Oguejiofor O.S, Okorogu V.N, Nwalozie G.C, Adewale Abe, Indoor Propagation Prediction in Wireless Local Area Network (WLAN) IJEIT Volume 2, Issue 4, October 2012
- [3] "MATLAB® V7.9.0.529 (R2009b), "Neurofuzzy computing based on fuzzy logic toolbox", Matlab works 2009," ed
- [4] F. D. Alotaibi, A. Abdennour, and A. A. Ali, "A robust prediction model using ANFIS based on recent TETRA outdoor RF measurements conducted in Riyadh city–Saudi Arabia," AEU-International Journal of Electronics and Communications, vol. 62, pp. 674-682, 2008.
- [5] Jyh-Shing Roger Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," IEEE Transactions on Systems, MAN, and Cybernetics, VOL.23, NO. 3, MAY/JUNE 1993
- [6] NNEBE Scholastica .U, "Pathloss Prediction Model of a Wireless Sensor Network in an Indoor Environment, IJAREEIE Vol. 3, Issue 9, September 2014"