Comparing the performance of ANFIS, PSO-ANFIS and PSO-ANFIS with random input in indoor Wi-Fi Signal propagation prediction

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Abstract-With the increase in the use of mobile devices fitted with wireless local area networks (WLANS) technologies there is need for accelerated studies on these systems to improve on the quality of service (QoS) provided to the users. Different methods have been used in signal modeling including deterministic and empirical models. This study is aimed at comparing the performance of predicting Wi-Fi signal propagation along a corridor using Particle Swarm Optimization (PSO) trained Adaptive Neural Fuzzy Inference System (ANFIS), ANFIS and PSO trained ANFIS with a random input. The mean square error, root mean square and standard deviation of the predicted signal were determined and compared. The study was undertaken using a Wi-Fi router as the transmitter and a mobile phone as the receiver in the process of data collection. The measured values were then used in the modeling. It was found that the predicted values based on PSO trained ANFIS with a random input were close to actual measured values as from the undertaken analysis giving the best prediction.

Keywords; Wi-Fi, QoS, WLANS, ANFIS, PSO-ANFIS

I. INTRODUCTION

Wi-Fi networks form one of the largest market segments of wireless networks. Coverage in line of sight (LOS) environments is limited both by physical obstacles and structural barriers, while in built environments, the main obstacles are walls [1]. What is common for both is interference in the wireless spectrum. The most commonly used ISM bands for Wi-Fi networks are at 2.4 GHz and 5 GHz, and the signals at such high frequencies do not easily pass through the obstacles. To increase connectivity and extend coverage, Wi-Fi networks use limited transmission powers, typically up to 100 mW. This gives connectivity of a few tens of meters, even through walls. At the same time, LOS connectivity may reach significantly greater distances, causing far away nodes to interfere in very unusual patterns.

ANFIS is one of the most current techniques used in function approximation besides other very many applications like classification. The technique is obtained by combining the Neural Networks and Fuzzy Logic concepts which are based on numerical analysis and natural language respectively [3].

PSO originally by Doctor Kennedy and Eberhart in 1995, used to train ANFIS and other AI processes is based on the intelligence of swarms as they move in search of food [9].

This study investigated the prediction of signal coverage of Wi-Fi networks using PSO trained ANFIS.

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A. Statement of the problem

WLANS are increasingly becoming a very important concept in our lives at home and work equally. Scientists have done various studies in regard to this technology and continue to do the same to ensure quality of service (QoS) is improved to the ever growing number of users. In view of this, the idea of also adding to the progressing research in this field led to this study. PSO trained ANFIS is commonly used in approximating functions because of their advantages that include high accuracy and better computational efficiency.

B. Research objectives

Main objective;

To Compare the performance of PSO trained ANFIS with a random input, PSO trained ANFIS and ANFIS.

Specific objectives

1. Measure signal strength with variation of distance along a corridor.
2. Obtain graphical comparisons for the performance of PSO trained ANFIS with a random input, PSO trained ANFIS and ANFIS.

II. LITERATURE REVIEW

A. Introduction

Wireless networking works by sending radio transmissions on specific frequencies where listening devices can receive them. The necessary radio transmitters and receivers are built into Wi-Fi enabled equipment like routers, laptops and phones. Antennas are also key components of these radio communication systems, picking up incoming signals or radiating outgoing Wi-Fi signals [4], [5]. Some Wi-Fi antennas, particularly on routers, may be mounted externally while others are embedded inside the device's hardware enclosure [2], [6].

ANFIS combines the advantages of both neural network and fuzzy logic in its operation resulting to a powerful tool in approximating functions [3].

PSO finds the optimal solution by simulating the social behavior of groups as fish schooling or bird flocking. A group can achieve the objective effectively by using the common information of every particle (global), and the information owned by the particle itself (personal) [9].

B. Other methods used in Wi-Fi signal prediction

1. COST231 One-Slope Model

Empirical models describe the signal level loss by empirical formulas with empirical parameters optimized by measurement campaigns in various buildings to make the empirical parameters of the model as universal as possible. The COST231 One-Slope model (OSM) is the simplest approach to signal loss prediction, because it is based only on the distance between the transmitter and the receiver. This simplest prediction model does not take into account the position of obstacles, the influence of which is respected only by the power decay factor (2). Factor n and the signal loss at a distance d_0 from the transmitter L(d) in equation (1) increase for a more lossy environment, but they are constant for the whole building [15], [16], [17].

$$L_{OSM} = (d_0) + n10\left(\frac{d}{d_0}\right) \qquad (1)$$

where: L_{OSM}..............Predicted signal loss (dB)
$L_0(d_0)$............Signal loss at distance d from transmitter (dB)
n....................Power decay factor (-)
d....................Distance between antennas (m)
d_0...................Reference distance between antennas (usually 1 m) (m)

2. Dual-Slope Model

The path loss in dB is given by experimentally.

$$L_{dB} = L_{0,dB} + \begin{cases} 10n_1 log_{10} d, \ 1m < d \le d_{bp} \\ 10n_1 log_{10} d + 10n_2 log_{10}\left(\frac{d}{d_{bp}}\right), \ d > d_{bp} \end{cases} \qquad (2)$$

Basically, this model divides the distances into one line-of-sight (LOS) and one obstructed LOS region. The break point distance d_{bp} takes into account that in indoor environments the ellipsoidal Fresnel zone can be obstructed by the ceiling or the walls, anticipating the LOS region:

$$d_{dp} = \frac{4h_b h_m}{\lambda} \qquad (3)$$

where h_b and h_m denote the shortest distance from the ground or wall of the access point (AP) and station (STA), respectively [25].

3. Partitioned Model

The path loss in dB is given by

$$L_{dB} = L_{0,dB} + \begin{cases} 20log_{10} d, \ 1m < d \le 10m \\ 20 + 30log_{10}\left(\frac{d}{10}\right), \ 10m < d \le 20m \\ 29 + 60log_{10}\left(\frac{d}{20}\right), \ 20m < d \le 40m \\ 47 + 120log_{10}\left(\frac{d}{40}\right), \ d > 40m \end{cases} \qquad (4)$$

This model uses pre-determined values for the path loss exponents and breakpoint distances, according to previous field measurement campaigns [15].

4. Average Walls Model

This model is based on the Cost-231 multi-wall except that the loss due to obstructing walls is aggregated in just one parameter L. Therefore, for a single floor environment, the path loss estimated by (5) is modified to

$$L_{dB} = 20log_{10} d + k_w L_w \qquad (5)$$

where k_w denotes the number of penetrated walls. In order to determine the parameter L_w, each wall obstructing the direct path between the receiver and the transmitter antennas must have its loss measured as follows.
The loss of the first wall in dB is given by:

$$L_1 = L - L_{0,dB} - 20log_{10} d \qquad (6)$$

Where $L_{0,dB}$ is the path loss obtained at 1 meter distant from the transmitter; L denotes the measured total loss from 1 meter distant after the obstructing wall. For the second wall the loss of the first wall also must be taken into account. Therefore, the loss in dB of the second obstructing wall can be estimated as

$$L_2 = L - L_{0,dB} - 20log_{10} d - L_1 \qquad (7)$$

Keeping on the above methodology, the ith wall loss is given by

$$L_i = L - L_{0,dB} - 20log_{10} d - \sum_{j=1}^{i=1} L_j \qquad (8)$$

where the sum spans the losses of walls obtained previously. After all wall losses of the environment had been obtained, then the wall losses average value is computed and assigned to the parameter L_w [15].

5. Multi-Wall Model

The OSM is insufficiently accurate for most applications, due to the usually inhomogeneous structure of building with long waveguiding corridors or large open spaces on one side and small complex rooms with many obstacles on the other side. For such cases, the more accurate, but still partly empirical, Multi Wall model (MWM) employing a site-specific building structure description can be used.
The Multi-Wall model takes into account wall and floor penetration loss factors in addition to the free space loss (9). The transmission loss factors of the walls or floors passed by the straight-line joining the two antennas are cumulated into the total penetration loss L_{Walls} (10) or L (11), respectively. Depending on the model, either homogenous wall or floor transmission loss factors or individual transmission loss factors can be used. The more detailed the description of the walls and floors, the better the prediction accuracy. The penetration losses are optimized as other empirical parameters from measurements, so they are not equal to the real obstacle transmission losses, but only correspond to the appropriate empirical attenuation factors of the obstacles.

$L_{MWM} = L_1 + 20log_{10}(d) + L_{Walls} + L_{Floors}$..............(9)
$L_{Walls} = \sum_{i=1}^{l} a_{w_i} k_{w_i}$...(10)
$L_{Walls} = a_f k_f$...(11)

L_{MWM}.........Predicted signal loss (dB)
L_1...............Free space loss at a distance of 1m from transmitter (dB)
L_{Walls}..........Contribution of walls to total signal loss (dB)
L_{Floors}.........Contribution of floors to total signal loss (dB)
a_{wi}..............Transmission loss factor of one wall of i-th kind (dB)
k_{wi}...............Number of walls of i-th kind (-)
I..................Number of wall kinds (-)
a_f................Transmission loss factor of one floor (dB)
k_f............Number of floors (-)

Since the MWM considers the positions and specific transmission loss factor of walls, its results are more accurate than those of OSM. However, the shadowing effect of more closely adjacent walls are often overestimated, because their cumulated transmission loss factors lead to very small values of predicted signal level behind these elements. In other words the real signal may not follow a straight-line between antennas, but it can go around the walls. The computation time of the MWM is also quite short, and the sensitivity of the model to the accuracy of the description of the building is limited due to the simple consideration of only the number of obstacles passed by a straight line.

6. Artificial Neural Networks

According to [2] indoor radio propagation is a very complex and difficult radio propagation environment because the shortest direct path between transmit and receive locations is usually blocked by walls, ceilings or other objects. Signals propagate along the corridors and other open areas, depending on the structure of the building. In modeling indoor propagation, the following parameters must be considered: construction materials (reinforced concrete, brick, metal, glass, etc.), types of interiors (rooms with or without windows, hallways with or without door, etc.), locations within a building (ground floor, n^{th} floor, basement, etc.) and the location of transmitter and receiver antennas (on the same floor, on different floors, etc.). An alternative approach to the field strength prediction in indoor environment is given by prediction models based on artificial neural networks.

During last years, Artificial Neural Networks (ANN) have experienced a great development. ANN applications are already very numerous. Although there are several types of ANN's all of them share the following features: exact analytical formula impossible; required accuracy around some percent; medium quantity of data to process; environment adaptation that allows them to learn from a changing environment and parallel structure that allows them to achieve high computation speed. All these characteristics of ANN's make them suitable for predicting field strength in different environments. The prediction of field strength can be described as the transformation of an input vector containing topographical and morphographical information (e.g. path profile) to the desired output value. The unknown transformation is a scalar function of many variables (several inputs and a single output), because a huge amount of input data has to be processed. Owing to the complexity of the influences of the natural environment, the transformation function cannot be given analytically. It is known only at discrete points where measurement data are available or in cases with clearly defined propagation conditions which allow applying simple rules like free space propagation, etc.

The problem of predicting propagation loss between two points may be seen as a function of several inputs and a single output [20]. The inputs contain information about the transmitter and receiver locations, surrounding buildings, frequency, etc while the output gives the propagation loss for those inputs. From this point of view, research in propagation loss modeling consists in finding both the inputs and the function that best approximate the propagation loss. Given that ANN's are capable of function approximation, they are useful for the propagation loss modeling. The feedforward neural networks are very well suited for prediction purposes because do not allow any feedback from the output (field strength or path loss) to the input (topographical and morphographical data).

The presented studies develop a number of Multilayer Perceptron Neural Networks (MLP-NN) and Generalized Radial Basis Function Neural Networks (RBF-NN) based models trained on extended data set of propagation path loss measurements taken in an indoor environment. The performance of the neural network based models is evaluated by comparing their prediction error (μ), standard deviation (σ) and root mean square error (RMS) between their predicted values and measurements data. Also a comparison with the results obtained by applying an empirical model is done [2]. A drawback with multilayered feed-forward networks that contain numerous neurons in each layer is the required training time. Furthermore, an overly complex ANN may lead to data overfitting and, hence, generalization problems [19].

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) otherwise referred to as Adaptive Network-based Fuzzy Inference System was proposed in [7]. ANFIS is a blend of Fuzzy Logic (FL) and Artificial Neural Network (ANN) that captures the strengths and offsets the limitations of both techniques for building Inference Systems (IS) with improved results and enhanced intelligence. Fuzzy logic is associated with the theory of fuzzy set, which relates to classes of objects with rough boundaries in which membership is a matter of degree. It is an extensive multivalued logical system that departs in concept and substance from the traditional multivalued logical systems. Much of fuzzy logic may be viewed as a platform for computing with words rather than numbers. The use of words for computing is closer to human intuition and exploits the tolerance for imprecision, thereby lowering the cost of the solution [8]. However, there are no known appropriate or well-established methods of defining rules and membership functions based on human knowledge and experience. Artificial Neural Networks are made up of simple processing elements operating concurrently. These elements model the biological nervous system, with the network functions predominantly determined by the connections between the elements. Neural

Networks have the ability to learn from data by adjusting the values of the connections (weights) between the elements. Merging these two artificial intelligence paradigms together offers the learning power of neural networks and the knowledge representation of fuzzy logic for making inferences from observations.

Basic ANFIS Architecture

The ANFIS architecture described here is based on type 3 fuzzy inference system (other popular types are the type 1 and type 2). In the type 3 inference system, the Takagi and Sugeno's (TKS) if-then rules are used [3]. The output of each rule is obtained by adding a constant term to the linear combination of the input variables. Final output is then computed by taking the weighted average of each rule's output. The type 3 ANFIS architecture with two inputs (x and y) and one output, z, is shown in Fig. 1.

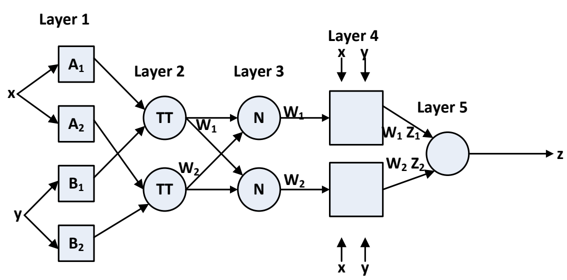

Fig. 1. Type 3 ANFIS Architecture.

$Rule\ 1: If\ x\ is\ A_1\ and\ y\ is\ B_1, then\ z_1 = p_1x + q_1y + r_1$
$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2, then\ z_2 = p_2x + q_2y + r_2$
The ANFIS structure is the functional equivalent of a supervised, feed-forward neural network with one input layer, three hidden layers and one output layer, whose functionality are as described below:

Layer 1 (Fuzzy Layer): Every node in this layer is an adaptive layer that generates the membership grades of the input vectors. Usually, a bell-shaped (Gaussian) function with maximum equal to 1 and minimum equal to 0 is used for implementing the node function:

$$O_i^1 = f(x, a, b, c) = \mu_{Ai}(x) = \frac{1}{1+|(x-c_i)/a_i|^{2b_i}}$$

$$\mu_{Ai}(x) = \exp\{-\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}\} \qquad (12)$$

Where O_i^1 is the output of the i^{th} node in the first layer, $\mu_{Ai}(x)$ is the membership function of input in the linguistic variable A_i. The parameter set $\{a_i, b_i, c_i\}$ are responsible for defining the shapes of the membership functions. These parameters are called premise parameters.

Layer 2 (Product Layer): Each mode in this layer determines the firing strength of a rule by multiplying the membership functions associated with the rules. The nodes in this layer are fixed in nature. The firing strength of a particular rule (the output of a node) is given by:

$$w_i = O_i^2 = \mu_{Ai}(x).\mu_{Bi}(y), i = 1, 2 \qquad (13)$$

Any other T-norm operator that performs fuzzy AND operation can be used in this layer.

Layer 3 (Normalized Layer): This layer consists of fixed nodes that are used to compute the ratio of the i^{th} rule's firing strength to the total of all firing strengths:

$$\overline{w} = O_i^3 = \frac{w_i}{w_1+w_2}, i = 1, 2, \qquad (14)$$

The outputs of this layer are otherwise known as normalized firing strength for convenience.

Layer 4 (Defuzzify Layer): This is an adaptive layer with node function given by:

$$\overline{w_i}z_i = O_i^4 = \overline{w_i}(p_ix + q_iy + r_i) \qquad (15)$$

This layer essentially computes the contribution of each rule to the overall output. It is defuzzification layer and provides output values resulting from the inference of rules. The parameters in this layer $\{p_i, q_i, r_i\}$ are known as consequent parameters.

Layer 5 (Total Output Layer): There is only one fixed node in this layer. It computes the overall output as the summation of contribution from each rule:

$$\sum_i \overline{w_i}z_i = O_i^5 = \sum_i \frac{w_iz_i}{\sum_i w_i} \qquad (16)$$

D. Particle Swarm Optimization (PSO)

PSO is a global optimization technique that was developed by Eberhart and Kennedy in 1995 [12], the underlying motivation of PSO algorithm was the social behavior observable in nature, such as flocks of birds and schools of fish in order to guide swarms of particles towards the most promising regions of the search space. PSO exhibits a good performance in finding solutions to static optimization problems where it is considered to be better than other algorithms like Genetic Algorithm [14]. It exploits a population of individuals to synchronously probe promising regions of the search space. In this context, the population is called a swarm and the individuals (i.e. the search points) are referred to as particles. Each particle in the swarm represents a candidate solution to the optimization problem. In a PSO system, each particle moves with an adaptable velocity through the search space, adjusting its position in the search space according to own experience and that of neighboring particles, then it retains a memory of the best position it ever encountered, a particle therefore makes use of the best position encountered by itself and the best position of neighbors to position itself towards the global minimum. The effect is that particles "fly" towards the global minimum, while still searching a wide area around the best solution [11]. The performance of each particle (i.e. the "closeness" of a particle to the global minimum) is measured according to a predefined fitness function which is related to the problem being solved. For the purposes of this research, a particle represents the weight vector of NNs, including biases. The dimension of the search space is therefore the total number of weights and biases [11].

The iterative approach of PSO can be described by the following steps:

Step 1: Initialize a population size, positions and velocities of agents, and the number of weights and biases.

Step 2: The current best fitness achieved by particle *p* is set as *pbest*. The *pbest* with best value is set as *gbest* and this value is stored.

Step 3: Evaluate the desired optimization fitness function f_p for each particle as the Mean Square Error (MSE) over a given data set.

Step 4: Compare the evaluated fitness value f_p of each particle with its *pbest* value. If f_p< pbest then pbest = f_p and $best_{xp} = x_p$, x_p is the current coordinates of particle p, and bestxp is the coordinates corresponding to particle *p's* best fitness so far.

Step 5: The objective function value is calculated for new positions of each particle. If a better position is achieved by an agent, *pbest* value is replaced by the current value. As in Step 1, *gbest* value is selected among *pbest* values. If the new *gbest* value is better than previous *gbest* value, the *gbest* value is replaced by the current *gbest* value and this value is stored. If f_p< gbest then gbest = p, where *gbest* is the particle having the overall best fitness over all particles in the swarm.

Step 6: Change the velocity and location of the particle according to Equations 9 and 10, respectively.

Step 7: Fly each particle p according to Equation 9.

Step 8: If the maximum number of predetermined iterations (epochs) is exceeded, then stop; otherwise Loop to step 3 until convergence.

$$V_i = wV_{i-1} + acc * rand() * \left(best_{xp} - xp\right) + acc * rand() * \left(best_{xgbest} - xp\right) \tag{17}$$

Where *acc* is the acceleration constant that controls how far particles fly from one another, and *rand* returns a uniform random number between 0 and 1.

$$xp = xpp + V_i \tag{18}$$

V_i is the current velocity, V_{i-1} is the previous velocity, xp is the present location of the particle, xpp is the previous location of the particle, and *i* is the particle index. In step 5 the coordinates bestxp and bestxgbest are used to pull the particles towards the global minimum [11].

Learning by PSO

To develop an accurate process model using ANFIS, the training, and validation processes are among the important steps. In the training process, a set of input-output patterns is repeated to the ANFIS. From that, weights of all the interconnections between neurons are adjusted until the specified input yields the desired output. Through these activities, the ANFIS learns the correct input-output response behavior [11].

The way PSO will be employed for updating the ANFIS parameters is explained in this section. The ANFIS has two types of parameters which need training, the antecedent part parameters and the conclusion part parameters. The membership functions are assumed Gaussian as in equation (3.4), and their parameters are $\{a_i, b_i, c_i\}$, where a_i is the variance of membership functions and c_i is the center of membership functions (MFs). Also is b_i a trainable parameter. The parameters of conclusion part are trained and here are represented with $\{p_i,\ q_i,\ r_i\}$ [11].

Applying PSO for Training ANFIS parameters

There are 3 sets of trainable parameters in antecedent part $\{a_i, b_i, c_i\}$, each of these parameters has N genes. Where, N represents the number of MFs. The conclusion parts parameters ($\{p_i,\ q_i,\ r_i\}$) also are trained during optimization algorithm. The fitness is defined as mean square error (MSE) [11].

Parameters are initialized randomly in first step and then are being updated using PSO algorithms. In each iteration, one of the parameters set are being updated i.e. in first iteration for example a_is are updated then in second $b_i$iteration are updated and then after updating all parameters again the first parameter update is considered and so on [11], [21].

Evaluation Criteria

The performance of the proposed approach will be evaluated by measuring the estimation accuracy. The estimation accuracy can be defined as the difference between the actual and estimated values. The first typical fitting criterion (MSE) is defined as in Equation 11:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{19}$$

where N is the total number of data, y is actual target value, and $\hat{y}$ its estimated target value.

The experiments will be implemented many times to ensure that MSE converges to a minimum value.

The initial values for weights will randomly be assigned within the range [-1; 1]. The training accuracy is expressed in terms of the mean absolute error, standard deviation (SD) and root mean squared error (RMSE). The absolute mean error (ME) is expressed as

$$e_i = |P_{measured} - P_{simulated}|, \quad \bar{e} = \frac{1}{N}\sum_{i=1}^{N} e_i, \tag{20}$$

where terms *measured* and *simulated* denote received signal strength that are obtained by measurement and simulated by ANFIS, while *N* is total number of samples. Standard deviation is given by

$$\sigma = \sqrt{\frac{1}{N-1}(e_i - \bar{e})^2} \tag{21}$$

The root mean squared error (RMSE) is calculated according to the expression

$$RMSE = \sqrt{\sigma^2 + \bar{e}^2} \qquad (22)$$

III. RESEARCH METHODOLOGY

A. *Practical Measurement of P_R*

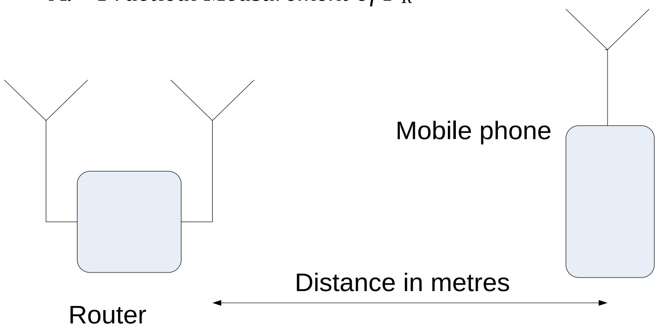

Fig. 2: Diagram of the experimental Set up

Fig. 3: Image for the experimental Set up

Fig. 4: Image for the experimental Set up in a corridor

The steps for carrying out the experiment are as follows;

i. A tape measure was used to measure a distance of 42m that was subdivided into 42 points each 1m apart.

ii. The Tecno R7 mobile device was moved metre by metre away from the D-link router and took the readings for every 1m to 42m.

B. *Data analysis*

For this study, the content analysis technique was employed to analyze the data. Matlab graphical representation techniques were used to analyze quantitative data. The full analysis on the key findings of this study is presented in the section below.

IV. FINDINGS AND DISCUSSIONS

A. *Results*

For the LOS case, the results were as shown in fig. 5 below;

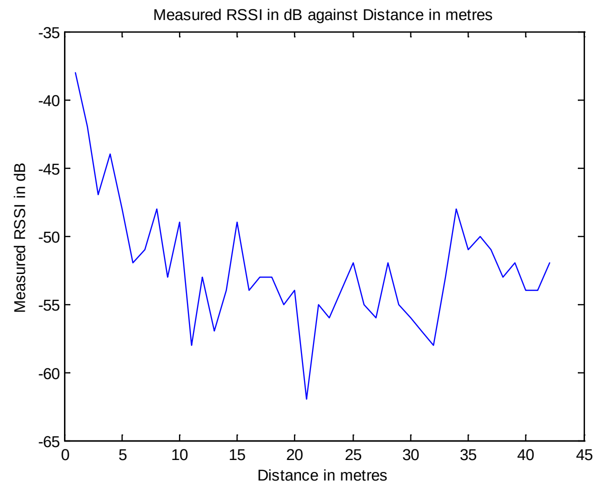

Fig. 5: LOS received signal variation with distance

Based on the measurement and Matlab analysis, the following graphs were generated for training and testing.

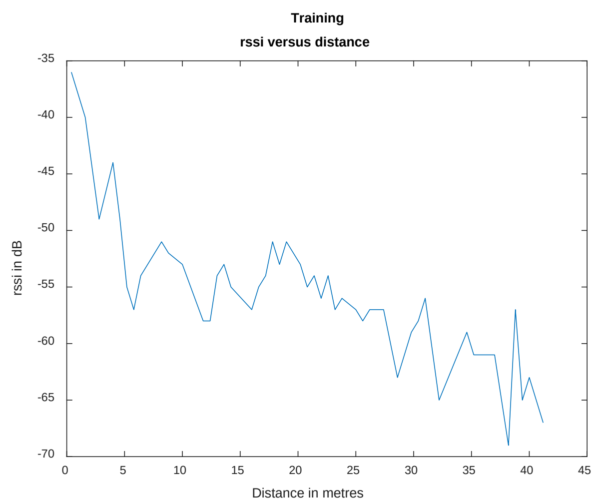

Fig. 6: Training LOS received signal variation with distance

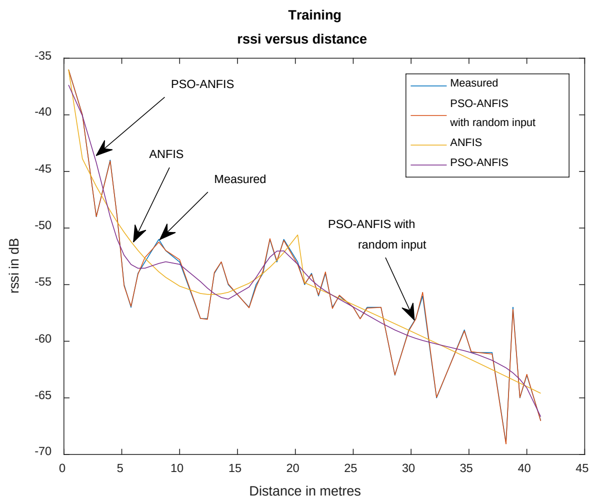

Fig. 7: Training Predicted and measured received signal variation with distance

TABLE I: TRAINING PARAMETERS

	MSE	RMSE	Standard deviation
ANFIS	6.6383	2.5765	1.6893
PSO-ANFIS	6.7002	2.3875	2.4127
PSO-ANFIS with random input	0.015114	0.12294	0.12422

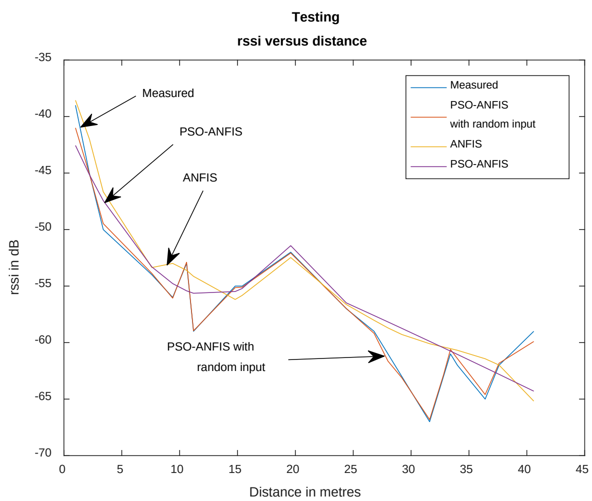

Fig. 8: Testing Predicted and measured received signal variation with distance

TABLE II: TESTING PARAMETERS

	MSE	RMSE	Standard deviation
ANFIS	7.709	2.7765	1.8682
PSO-ANFIS	8.7614	2.9583	2.6985
PSO-ANFIS with random input	0.30325	0.55068	0.55915

The graphs generated using the values obtained during the experiment and predicted are as shown above. The signal strength reduces gradually as expected due to the increase in distance between the transmitter and the receiver. For LOS propagation the time graphs show a variation in signal strength. This is due to variations in the channel conditions. The channel's transfer characteristics may vary due to movements of the transmitter, receiver or people in the indoor environment. The transmitted signal may reach the receiver through multiple reflected paths. These reflected signals may add up to strengthen each other or they may add up to cancel each other. Also, presence of objects in the path between the transmitter and the receiver also reduces the signal power arriving at the receiver. All this manifest themselves in the fluctuations in the power levels of different received signals.

This manifests in the first graph which has variations from the first to the last points.

Fig. 7 is the training predicted signal using PSO trained ANFIS with a random input, PSO trained ANFIS and ANFIS prediction tools. The variation is smooth trying to follow the actual measured values for PSO trained ANFIS with a random input tool. The same applies to the testing graph as shown in fig. 8. The different parameters obtained by comparing the measured and predicted values for the training and testing plots are given as;

The training, mean square error (MSE) was obtained as 0.015114, root mean squared error (RMSE) as 0.12294 and standard deviation (SD) as 0.12422 for PSO trained ANFIS with a random input, 6.7002, 2.3875 and 2.4127 for PSO trained ANFIS and 6.6383, 2.5765 and 1.6893 for ANFIS while the testing mean square error (MSE) was obtained as 0.30315, root mean squared error (RMSE) as 0.55068 and standard deviation (SD) as 0.55915 for PSO trained ANFIS with a random input, 8.7614, 2.9583 and 2.6985 for PSO trained ANFIS and 7.709, 2.7765 and1.8682 for ANFIS.

V. CONCLUSIONS AND RECOMMENDATIONS

A. *Conclusion*

From experiment and calculations performed as a result thereof, it can be stated that the power of a signal transmitted in free space decreases with increase in distance from the source for both predicted and measured values.

The values obtained above indicate the closeness of predicted to the measured values indicating that the PSO trained ANFIS is very accurate in modelling wireless prediction.

B. *Limitations of the study*

The major limitation of the study was random behavior of the received signal.

C. *Areas of further study*

Future research should include the use of different training methods and compare the resulting parameters.

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