Indoor LOS Wi-Fi Signal Coverage Modeling Using PSO Trained LOG10D-ANFIS with Random Input

Omae M O, Ndungu E N and Kibet P L
Department of Telecommunication and Information Engineering
Jomo Kenyatta University of Agriculture & Technology
Nairobi, Kenya

Abstract—Wireless local area networks (WLANS) are becoming very popular in our daily communications applications. Currently in kenya a number of internet service providers like Safaricom, Zuku and others are providing internet access using Wi-Fi. I believe this is replicated world over. This has necessitated studies on these systems to improve on the quality of service (QoS) provided to the users. Different methods have been used in signal propagation modeling. This study is aimed at predicting Wi-Fi signal propagation along a corridor using Particle Swarm Optimization (PSO) trained modified Adaptive Neural Fuzzy Inference System (ANFIS) that is LOG10D-ANFIS. The root mean square and standard deviation of the predicted signal were determined. 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 PSO trained LOG10D-ANFIS with random input modeling. It was found that the predicted values were close to actual measured values as from the undertaken analysis.

Keywords; Wi-Fi, QoS, WLANS, LOG10D-ANFIS

1 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, line-of-sight 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 LOG10D-ANFIS with random input.

Omae M O, Ndungu E N, Kibet P L School of Electrical, Electronic and Information Engineering, Department of Telecommunication & Information Engineering, JKUAT; e-mail: m_oteri@yahoo.com, ndunguen@yahoo.com, kibetlp@yahoo.com).

1.1 Statement of the problem

WLANS are currently becoming a very important concept in our lives. 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 the study of prediction of Wi-Fi signal using ANFIS which is commonly used in approximating functions because of its advantages that include high accuracy and better computational efficiency. In this study we used a slightly modified ANFIS trained with PSO (PSO trained LOG10D-ANFIS).

1.2 Research objectives

Main objective;
To predict Wi-Fi signal coverage using PSO trained LOG10D-ANFIS with random input.
Specific objectives;

1. Measure signal strength with variation of distance along a corridor.
2. Use PSO trained LOG10D-ANFIS with random input to model the measured signal.
3. Obtain graphs comparing the performance of PSO trained LOG10D-ANFIS with random input and ANFIS models.

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4. Obtain the RMSE, ME and SD values comparing the performance of PSO trained LOG10D-ANFIS with random input and ANFIS models on measured data.

2 LITERATURE REVIEW

2.1 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. Some Wi-Fi antennas, particularly on routers, may be mounted externally while others are embedded inside the device's hardware enclosure [2].

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].

2.2 Effect of distance

Signal attenuation over distance is observed when the mean received signal power is attenuated as a function of the distance from the transmitter. The most common form of this is often called free space loss and is due to the signal power being spread out over the surface area of an increasing sphere as the receiver moves farther from the transmitter.

In addition to free space loss effects, the signal experiences decay due to ground wave loss although this typically only comes into play for very large distances (on the order of kilometers) [2].

2.3 Multipath Propagation

Multipath results from the fact that the propagation channel consists of several obstacles and reflectors. Thus, the received signal arrives as an unpredictable set of reflections and/or direct waves each with its own degree of attenuation and delay. The delay spread is a parameter commonly used to quantify multipath effects. Multipath leads to variations in the received signal strength over frequency and antenna location [5].

2.4 Rate of fading

Time variation of the channel occurs if the communicating device (antenna) and components of its environment are in motion. Closely related to Doppler shifting, time variation in conjunction with multipath transmission leads to variation of the instantaneous received signal strength about the mean power level as the receiver moves over distances on the order of less than a single carrier wavelength.

The degree of time variation in an outdoor system is much more than that of an indoor system. One manifestation of time variation is as spreading in the frequency domain (Doppler spreading). The frequency in our case varied from 2412 to 2467 MHz.

2.5 Free space path loss

Free space path loss (FSPL) is the loss in signal strength that occurs when an electromagnetic wave travels over a line of sight (LOS) path in free space. In such a circumstance, there are no obstacles that might cause the signal to be reflected, refracted or that might cause additional attenuation [4].

When calculating thus, factors relating to the transmitter power, antenna gains or the receiver sensitivity levels are not considered and only the loss along the path itself is considered. As a signal moves away from the transmitter, it keeps spreading out in the form of a sphere increasing the sphere's surface area with increase in distance thus, the intensity of the signal decreases. It can be deduced that the signal decreases in a manner that is inversely proportional to the square of the distance from the source of the radio signal in free space.

Losses are experienced in radio wave communication links as the signal is sent from the source to the destination. One type of such losses is path losses. These occur due to effects along the transmission media. Under path losses we have free space losses among others [5]. These are highly affected by variation of distance and frequency.

The received power at the destination in dB is given by:-

$$P_R = P_t G_t G_R / (4\pi d/\lambda)^2 \quad (1)$$

$$P_R = P_{t\,dB} + G_{t\,dB} + G_{R\,dB} - FSL_{dB} \quad (2)$$

P_R is received power
P_t is the transmitted power
G_t is the transmitter gain
G_R is receiver gain

This is referred to as Friis equation which is the link equation. Most RF comparisons and measurements are performed in decibels. This gives an easy and consistent method to compare the signal levels present at various points. Accordingly, it is very convenient to express the free space path loss formula, FSPL, in terms of decibels. It is easy to take the basic free space path loss equation and manipulate into a form that can be expressed in a logarithmic format [7].

Free space losses (FSL) is given by:-

$$FSL = 32.44 + 20\log d + 20\log f \quad (3)$$

Where;

FSL= free space losses in dB
d= distance between the source and destination in kms
f= frequency

In this work, the apparatus used have the following specifications:

Mobile Phone Receiver

Tecno R7 with G(r) as +4dB was used.

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D-Link DIR 605L router (Transmitter)
P (t) = +15dBm; G (t) = +4dBi
Therefore, P (D-Link) = 15 + 4 + 4 = +23dB.

The fundamental design of and plan of indoor wireless network depends on the measurement and analysis of the Wi-Fi signal. Distance is one of the major contributors of the attenuation of the radio signal propagation known as the path loss [6]. The signal received by the user reduces in power with the distance it traverses following an inverse square law. For an ideal condition the power of the signal is given by eq. (2).

2.6 Other losses

Apart from free spaces there are other losses that contribute to the reduction of the received signal strength that include atmospheric losses, antenna misalignment, polarization mismatch and losses due a number of path obstacles like walls, people and furniture [5].

3 Proposed Model

3.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) was first proposed by Jang in [7]. It combines the two concepts Fuzzy Logic (FL) and Artificial Neural Network (ANN) which captures their strengths and reduces the limitations of both techniques for building Inference Systems (IS) with better results. The Fuzzy logic concept deals with fuzzy set theory that relates to classes of objects with boundaries whose membership is a matter of degree. It can also be seen as a platform that computes with words instead of numbers which is closer to human language and makes use of tolerance for imprecision, thus lowering the solution cost [8]. As indicated in 9) above Artificial Neural Networks consist of interconnected simple processing elements that operate simultaneously in parallel modeling the biological nervous system. These networks are able to learn from input data by modifying the values of the connections referred to as weights between the elements as the error is reduced. These two artificial intelligence based concepts when merged together they offer the fuzzy logic knowledge representation that makes inferences from observations and the neural networks learning capability. This results to a very powerful system with many applications including function approximation which we are using it for [23].

3.2 Basic ANFIS Architecture

The ANFIS architecture used in this research is based on type 3 fuzzy inference system (other popular types are the type 1 and type 2) [22]. 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. The final output is then computed by taking the weighted average of each rule's output. This type 3 ANFIS architecture with two inputs (x and y) and one output, z, is shown in Fig. 1.

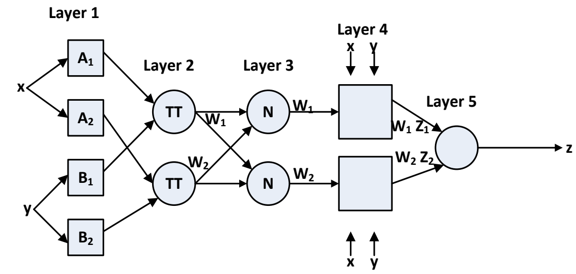

Fig. 1. Type 3 ANFIS Architecture.

The ordinary rule representation of the ANFIS is given as:

$$Rule\ 1: If\ x\ is\ A_1\ and\ y\ is\ B_1, then\ z_1 = p_1x + q_1y + r_1$$
$$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2, then\ z_2 = p_2x + q_2y + r_2$$

3.3 PSO trained LOG10D-ANFIS with random input model proposed model

The improved ANFIS with two inputs distance (x) and a random input (y) representing random RSSI and one output, RSSI (z), is shown in Fig. 2. The distance input is passed through a logarithmic function before it goes to layer 1 while the other input goes direct where the premise parameters are modified using PSO. In layer 4 where the consequent parameters are modified using PSO, the distance input x is also passed through the logarithmic function while the random RSSI input goes in direct.

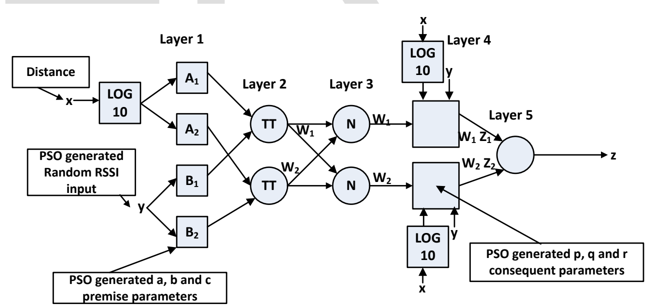

Fig. 2. PSO trained ANFIS structure with two inputs distance and random RSSI.

$$Rule\ 1: If\ log10x\ is\ A_1\ and\ y\ is\ B_1 then\ z_1 = p_1log10x + q_1y + r_1$$

$$Rule\ 2: If\ log10x\ is\ A_2\ and\ y\ is\ B_2\ then\ z_2 = p_2log10x + q_2y + r_2$$

x=distance, y=random input and z=rssi

y is a random input which also shows the adaptability of the system-output modelled to vary according to the y random input.

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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:

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

$$\mu_{\,Ai}(x) = \exp\{-\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}\} \qquad (30)$$

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:

$$w_i = O_i^2 = \mu_{Ai}(x).\,\mu_{Bi}(y), i = 1, 2 \qquad (31)$$

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:

$$\overline{w} = O_i^3 = \frac{w_i}{w_1+w_2}\ , i = 1, 2, \qquad (32)$$

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:

$$\overline{w_i} z_i = O_i^4 = \overline{w_i}(p_i x + q_i y + r_i) \qquad (33)$$

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:

$$\sum_i \overline{w_i} z_i = O_i^5 = \sum_i \frac{w_i z_i}{\sum_i w_i} \qquad (34)$$

3.4 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.

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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 (35) and (36), respectively.
Step 7: Fly each particle p according to Equation (35).
Step 8: If the maximum number of predetermined iterations (epochs) is exceeded, then stop; otherwise Loop to step 3 until convergence.

$$V_i = wV_{i-1} + acc * rand() * \left(best_{xp} - xp\right) + acc * rand() * \left(best_{xgbest} - xp\right) \qquad (35)$$

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.

$$xp = xpp + V_i \qquad (36)$$

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].

3.5 ANFIS learning by PSO

The training and validation processes are among the important steps used to develop an accurate process model using ANFIS where a set of input-output patterns is repeated to the ANFIS in the training process [10]. The weights of all the interconnections between neurons are adjusted repeatedly until the specified input yields the desired output. From these iterations, the ANFIS learns the right input-output response behavior [11]. PSO is employed for updating the ANFIS parameters where ANFIS has two types of parameters which need training i.e. the antecedent part parameters and the conclusion part parameters. It is assumed that the membership functions are Gaussian as in equation 30, and their parameters are $\{a_i, b_i, c_i\}$, where a_i is the variance of membership functions, c_i is the center of membership functions (MFs) and b_i a trainable parameter. The parameters $\{p_i,\ q_i,\ r_i\}$ of conclusion part are also trained [11],[15].

3.6 Applying PSO for Training ANFIS parameters

As indicated above there are 3 sets of trainable parameters in antecedent part $\{a_i, b_i, c_i\}$ where each of these parameters has N particles which represents the number of MFs. The conclusion parameters ($\{p_i,\ q_i,\ r_i\}$) are also trained during optimization algorithm. They are also N particles, where the fitness is defined as root mean square error (RMSE) [11]. In the first step the parameters are initialized randomly after which they are updated using PSO algorithms. The parameters sets are being updated in each iteration according to the fitness function RMSE [11], [21]. This is as represented in fig. 3.

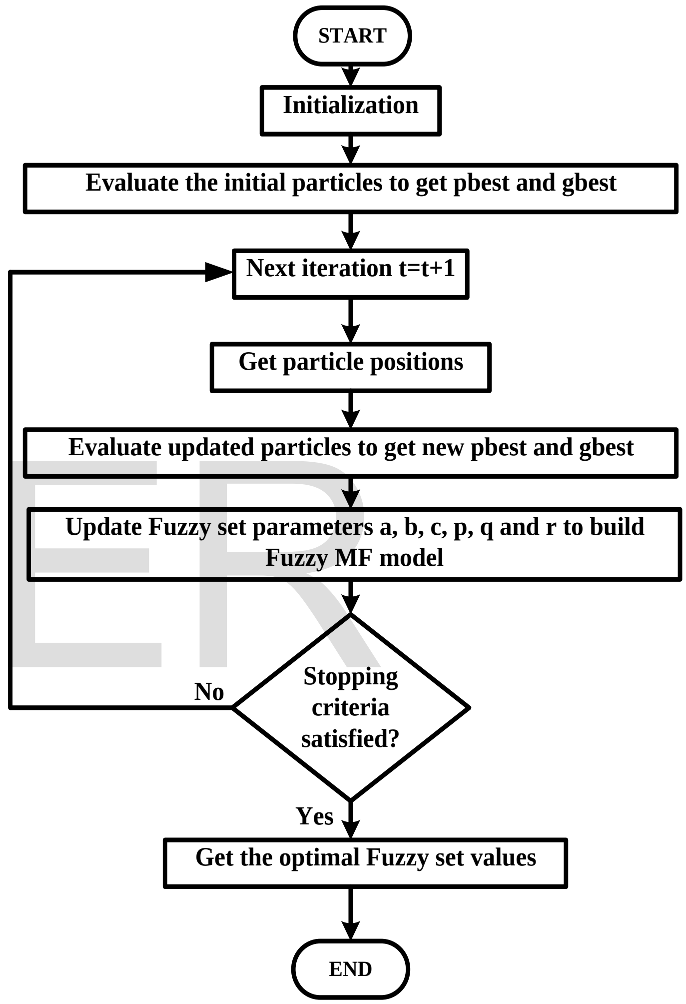

Fig. 3: ANFIS training with PSO flowchart

3.7 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 (37):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (37)$$

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

$$e_i = \left|P_{target} - P_{simulated}\right|, \bar{e} = \frac{1}{N}\sum_{i=1}^{N} e_i, \quad (38)$$

where terms *target* and *simulated* denote received signal strength that are obtained by model under cosideration and simulated by PSO trained modified ANFIS, while N is total number of samples. Standard deviation is given by

$$\sigma = \sqrt{\frac{1}{N-1}(e_i - \bar{e})^2} \quad (39)$$

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

$$RMSE = \sqrt{\sigma^2 + \bar{e}^2} \quad (40)$$

3.8 Practical Measurement of P_R

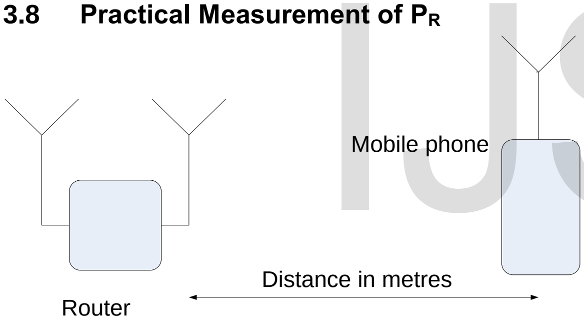

Fig. 4: Diagram of the experimental Set up


Fig. 5: Image for the experimental Set up


Fig. 6: 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 from the router.

This is indicated in figures 4, 5 and 6.

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.

4 FINDINGS AND DISCUSSIONS

4.1 Results

For the LOS case, the results were as shown in fig. 7 below;

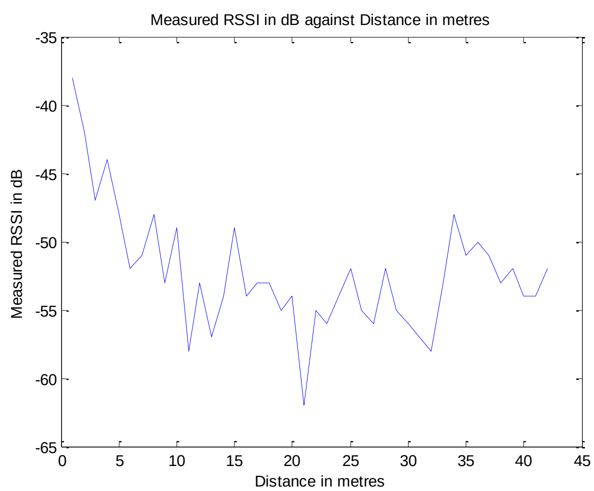

Fig. 7: LOS received signal variation with distance

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

TABLE I: TRAINING PARAMETERS

	RMSE	ME	Standard deviation
ANFIS	2.2825	1.7659	1.4621
PSO-ANFIS with random input	0.0026	0.0016	0.0021

TABLE II: TESTING PARAMETERS

	RMSE	ME	Standard deviation
ANFIS	2.9123	2.1874	1.9660
PSO-ANFIS with random input	2.9310	2.4028	1.7162

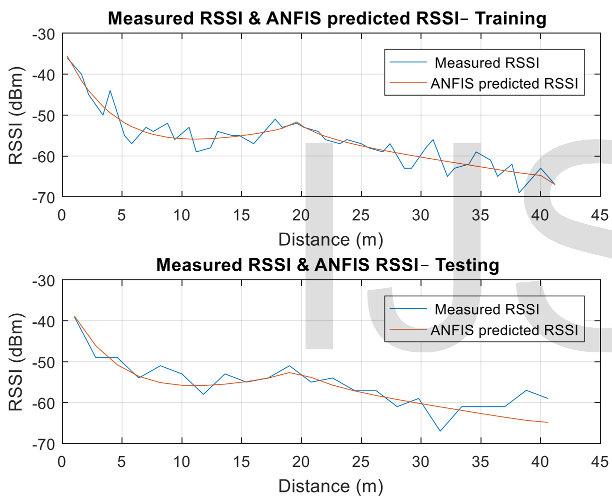

Fig. 8: Measured and ANFIS training and testing

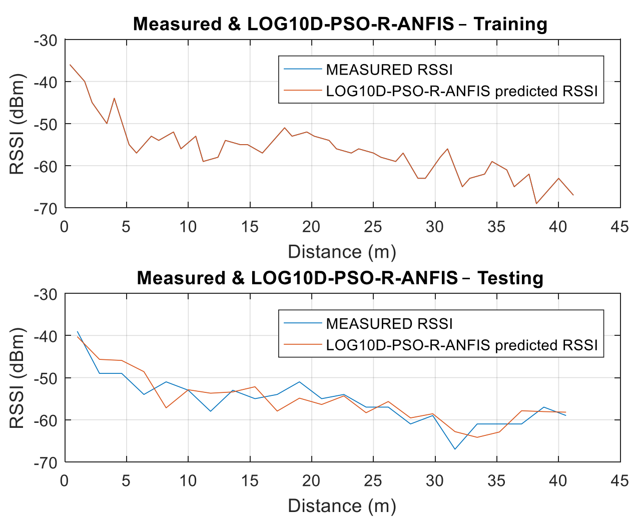

Fig. 9: Measured and LOG10D-PSO-R-ANFIS training and testing

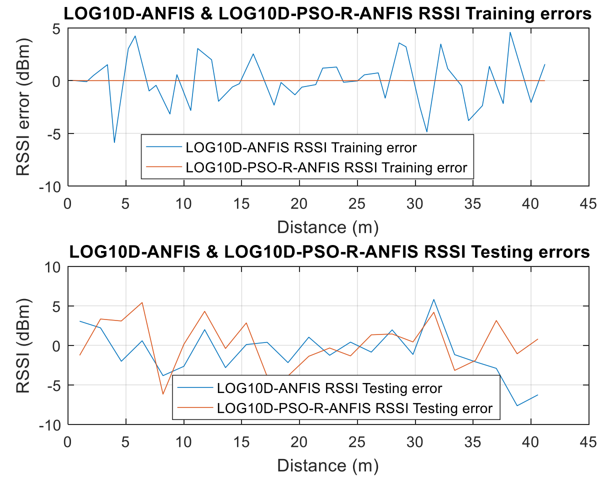

Fig. 10: Measured ANFIS and LOG10D-PSO-R-ANFIS training and testing errors

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. 8 is the ANFIS training and testing prediction tool compared with the measured. The variation is not following the actual measured values. The variation in fig. 9 is smooth closely following the measured values for training. 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 0.0026, root mean squared error (RMSE) as 0.0016 and standard deviation (SD) as 0.0021 using the proposed method 2.2825, 1.7659 and 1.4621 respectively using ANFIS while the testing mean square error (MSE) was obtained as 2.9310, root mean squared error (RMSE) as 2.4028 and standard deviation (SD) as 1.7162 using the proposed method while for ANFIS 2.9123, 2.1874 and 1.9660 were obtained.

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5 CONCLUSIONS AND RECOMMENDATIONS

5.1 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 LOG10D-ANFIS with random input is very accurate in modelling wireless prediction.

5.2 Areas of further study

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

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