Indoor LOS Wi-Fi Coverage Prediction using ANN

Omae M. O, Ndungu E. N and Kibet P. L.

Abstract-Wi-Fi communication standard is becoming very popular and important in our daily communications applications. As a result research is being undertaken to improve on its quality of service (QoS). This study is aimed at predicting Wi-Fi signal propagation along a corridor using Artificial Neural Networks (ANN). The absolute mean error (ME), root mean square error 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. The measured values were then used in ANN prediction.
Keywords; Wi-Fi, QoS, RMSE, ANN

I. INTRODUCTION

Wireless fidelity (Wi-Fi)is a higher power bandwidth communication technique used to develop wireless LANs. Developed and managed under the IEEE 802.11 standard. The generations for Wi-Fi include 802.11, 802.11a, 802.11b up to 802.11g except L, M and Z.

Its 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 unlicensed 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. Additional features include distance of up to 100m but can be extended to 1km. Also power dissipation and consumption is higher than Bluetooth. ANN is one of the most current techniques used in function approximation besides other very many applications like classification. The technique is based on numerical analysis imitating the human brain operation.

This study investigated the prediction of signal coverage of Wi-Fi networks using ANN.

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A. *Statement of the problem*

Wireless telecommunication technologies 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) 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 ANN which is commonly used in approximating functions because of its advantages.

B. *Research objectives*

Main objective;
To predict Wi-Fi signal coverage using ANN.

Specific objectives
1. Measure signal strength with variation of distance along a corridor.
2. Use ANN to predict the measured signal.

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

Also ANN is a powerful tool in approximating functions where it uses mathematical neuron modelling [3].

B. *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).

C. *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.

D. 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). In this study the frequency is varied from 2412 to 2467 MHz.

E. 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 radiowave 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 radio frequency (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.

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 research, the apparatus used have the following specifications:

Mobile Phone Receiver

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

D-Link DIR 605L router (Transmitter)

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

The fundamental design 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

$P_R = P_{t\,dB} + G_{t\,dB} + G_{R\,dB} - FSL_{\,dB}$
Where P_R is the power transmitted
P_t is power of the router
G_t is the gain of the router
G_R is the antennae gain for the mobile device/laptop

FSL is given by $32.44 + 20logd + 20logf$ where d is the distance in km and f is the frequency in MHz [7].

F. Artificial Neural Networks (ANNs)

According to [7] 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 and others), types of interiors (rooms with or without windows, hallways with or without door and others), locations within a building (ground floor, n^{th} floor, basement and others) and the location of transmitter and receiver antennas (on the same floor, on different floors and others). 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 (for example 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 and others.

The problem of predicting propagation loss between two points may be seen as a function of several inputs and a single output [8]. 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 feed forward neural networks are very well suited for prediction purposes because they 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 (RMSE) between their predicted values and measurements data. Also a comparison with the results obtained by applying an empirical model is done [1]. 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 [9].

G. The ANN Overview

Multilayer Perceptron Neural Network (MLP-NN)

Fig. 1 shows the configuration of a multilayer perceptron with one hidden layer and one output layer. The network shown here is fully interconnected.

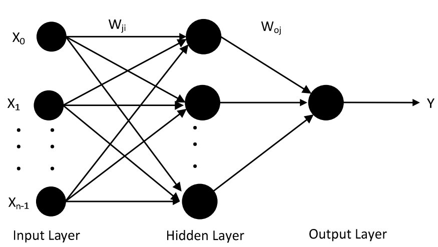

Fig. 1. Configuration of the MLP-NN

This means that each neuron of a layer is connected to each neuron of the next layer so that only forward transmission through the network is possible, from the input layer to the output layer through the hidden layers. Two kinds of signals are identified in this network:

The function signals (also called input signals) that come in at the input of the network, propagate forward (neuron by neuron) through the network and reach the output end of the network as output signals;

The error signals that originate at the output neuron of the network and propagate backward (layer by layer) through the network. The output of the neural network is described by the following equation:

$$y = F_o\left(\sum_{j=0}^{M} W_{oj}\left(F_h\left(\sum_{i=0}^{n} W_{ji} X_i\right)\right)\right) \quad (4)$$

where:

- W_{oj} represents the synaptic weights from neuron j in the hidden layer to the single output neuron,
- X_i represents the i^{th} element of the input vector,
- F_h and F_o are the activation function of the neurons from the hidden layer and output layer, respectively,
- $W_{ji}$are the connection weights between the neurons of the hidden layer and the inputs.

The learning phase of the network proceeds by adaptively adjusting the free parameters of the system based on the mean squared error E, described by (5), between predicted and measured path loss for a set of appropriately selected training examples:

$$E = \frac{1}{2}\sum_{i=1}^{m}(y_i - d_i)^2 \quad (5)$$

Where y_i is the output value calculated by the network and d_i represents the expected output.

When the error between network output and the desired output is minimized, the learning process is terminated and the network can be used in a testing phase with test vectors. At this stage, the neural network is described by the optimal weight configuration, which means that theoretically it ensuresoutput error minimization [8].

Generalized Radial Basis Function Neural Network (RBF-NN)

The Generalized Radial Basis Function Neural Network (RBF-NN) is a neural network architecture that can solve any function approximation problem.

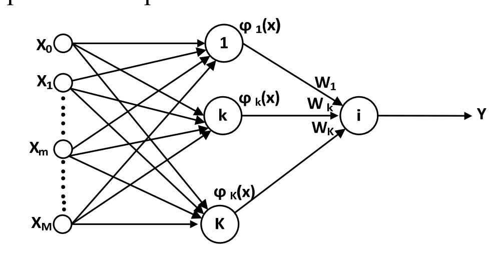

Fig.2. RBF-NN architecture

The learning process is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data, with the criterion for the "best fit" being measured in some statistical sense. The generalization is equivalent to the use of this multidimensional surface to interpolate the test data. As it can be seen from Fig. 2, the Generalized Radial Basis Function Neural Network (RBF–NN) consists of three layers of nodes with entirely different roles:

- The input layer, where the inputs are applied,

- The hidden layer, where a nonlinear transformation is applied on the data from the input space to the hidden space; in most applications the hidden space is of high dimensionality.
- The linear output layer, where the outputs are produced

The most popular choice for the function φ is multivariate Gaussian function with an appropriate mean and auto covariance matrix.

The outputs of the hidden layer units are of the form

$$\varphi_k[X] = exp[-(X - V_k^x)^T(X - V_k^x)/(2\sigma^2)] \qquad (6)$$

Where V_k^x are the corresponding clusters for the inputs and V_k^y are the corresponding clusters for the outputs obtained by applying a clustering technique of the input/output data that produces K cluster centres. The parameter σ controls the "width" of the radial basic function and is commonly referred to as the spread parameter.

V^y_k is defined as

$$V_k^y = \sum_{y(p)\in \, cluster \, k} y(p) \qquad (7)$$

The outputs of the hidden layer nodes are multiplied with appropriate interconnection weights to produce the output of the GRNN. The weight for the hidden node k (that is w_k) is equal to

$$W_k = V_k^y / \sum_{k=1}^{k} N_k exp\left[-\frac{d(x,V_k^x)^2}{2\sigma^2}\right] \qquad (8)$$

N_k is the number of input data in the cluster centre k, and

$$d(X, V_k^x) = (X - V_k^x)^T(X - V_k^x) \qquad (9)$$

With

$$V_k^x = \sum_{x(p)\in \, cluster \, k} x(p) \qquad (10)$$

H. 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 (11):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(P_{measured} - P_{predicted}\right)^2 \qquad (11)$$

whereN is the total number of data, $p_{measured}$ is actual target value, and$p_{predicted}$ its estimated target value.

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

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

$$e_i = \left|P_{measured} - P_{predicted}\right|,$$
$$\bar{e} = \frac{1}{N}\sum_{i=1}^{N} e_i, \qquad (12)$$

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

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|e_i - \bar{e}|,^2} \qquad (13)$$

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

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{measured} - P_{predicted}\right)^2} \qquad (14)$$

III. RESEARCH METHODOLOGY

A. Practical Measurement of P_R

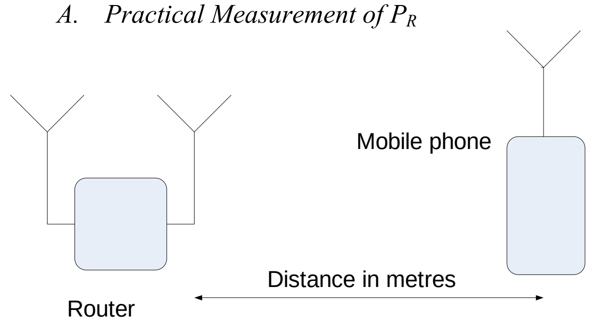

Fig. 3: Diagram of the experimental Set up


Fig.4:Imagefor the experimental Set up

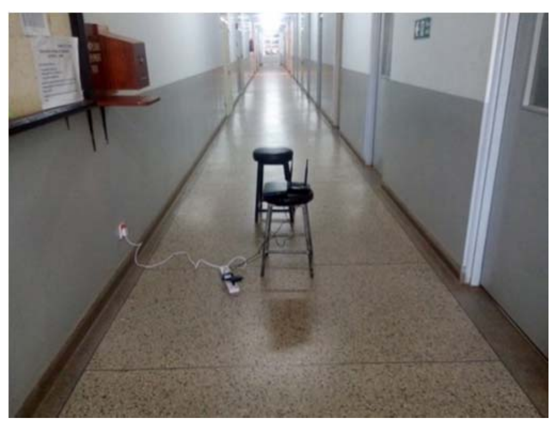
Fig.5:Imageof the experimental Set up in a corridor

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 for the D-link router and took the readings for every 1m from the router in Table 1.

B. *Data analysis*

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

IV. FINDINGS AND DISCUSSIONS

A. *Results*

For the LOScase, the results were as shown in Table 1;

TABLE 1:RECEIVED POWER MEASUREMENTS

Distance (m)	P_R Value (dBm)
1	-38
2	-42
3	-47
4	-44
5	-48
6	-52
7	-51
8	-48
9	-53
10	-49
11	-58
12	-53
13	-57
14	-54
15	-49
16	-54
17	-53
18	-53
19	-55
20	-54
21	-62
22	-55
23	-56
24	-54
25	-52
26	-55
27	-56
28	-52
29	-55
30	-56
31	-57
32	-58
33	-53
34	-48
35	-51
36	-50
37	-51
38	-53
39	-52
40	-54
41	-54
42	-52

Based on the measurement Matlab analysis, the following graphs were generated.

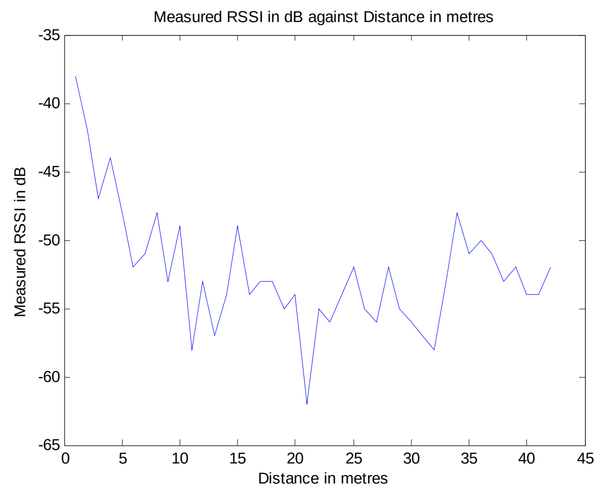

Fig. 6: LOS received signal variation with distance

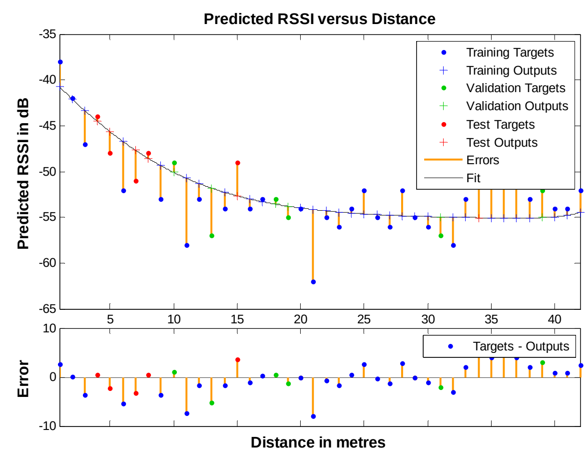

Fig. 7: Predicted signal variation with distance and error

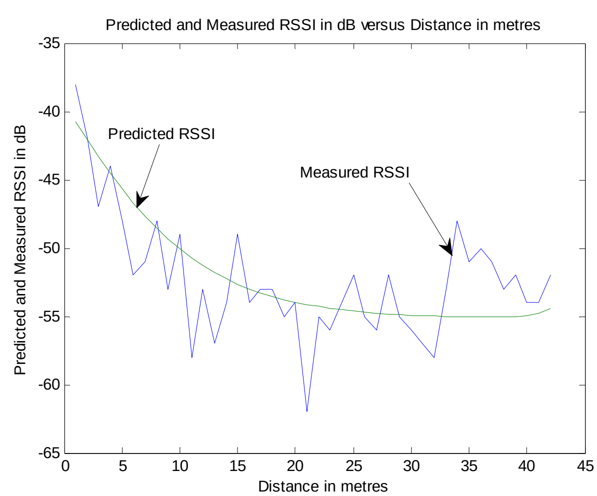

Fig. 8:Predicted and measured received signal variation with distance

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 LOSpropagationthe 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. 5 shows the predicted signal using ANN prediction tool. The variation is smooth as shown in the graph.Thedifferent parameters obtained by comparing the measured and predicted values for the third plot are given as;
The absolute mean error (ME) was obtained as 2.4127, root mean squared error (RMSE) as 3.1311 andstandard deviation (SD) as 2.0199.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusion

From the analysis of the experimental data collected, it is found that the power of a signal transmitted in free space decreases with increase in distance from the source for both predicted and measured values. It can also be noted that ANN predicted signal tries to follow a smooth curve based on the previous and the values after.

From the study the following values were obtained; absolute mean error (ME)=2.4127, root mean squared error (RMSE)as 3.1311 andstandard deviation (SD) as 2.0199.

B. Areas of further study

Future research should include the use different training methods to compare the resulting parameters with those obtained under the default training methods. Also comparison between ANN and other prediction methods like ANFIS.

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