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A Universal Wireless Signal Propagation Prediction Model Based on PSO Trained Modified ANFIS

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Abstract— With the increase in the use of mobile devices, 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 developing a universal wireless prediction model using Particle Swarm Optimization (PSO) trained modified Adaptive Neural Fuzzy Inference System (LOG10D-ANFIS) being an improvement to the original ANFIS structure for wireless communication propagation. This model is to combine all the deterministic and empirical models used in wireless propagation into one. In our study we have used eight of the models, as discussed under literature section, to show that this is possible. The mean square error (MSE), root mean square error (RMSE) and standard deviation (SD) of the predicted signal were determined and compared. The developed model, is very accurate in approximating the other models where we are getting errors of up to 10^{-15}. Also this universal model eliminates the necessity of many input parameters associated with the individual models resulting to a requirement of just one input that is distance. This should be a big advantage to software developers who can use this model to come up with simulators for wireless propagation prediction.

Keywords; QoS, ANFIS, PSO, LOG10D-ANFIS

1 Introduction

Wireless networks form one of the largest market segments of communication systems. 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 bands for wireless networks do not easily pass through the obstacles.

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 wireless networks using various models. From these models a single universal model based on PSO trained modified ANFIS was developed.

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1.1 Statement of the problem

Wireless communication is increasingly becoming a very important concept in our lives at home and work equally. Scientists have done and are still doing various studies in regard to their use and continue to do the same to ensure quality of service (QoS) is improved to the ever growing number of users. However, all the known research undertaken in literature is based on single independent models. In view of this, the idea of also adding to the progressing research in this field led to this study. This led to the development of a universal model based on PSO trained modified ANFIS (LOG10D-ANFIS).

1.2 Research objectives

Main objective is aimed at developing a universal wireless prediction model using Particle Swarm Optimization (PSO) trained Adaptive Neural Fuzzy Inference System (ANFIS).

Specific objectives

1. Analyze the different existing theoretical models.
2. Obtain graphs comparing the performance of PSO trained LOG10D-ANFIS, LOG10D-ANFIS and ANFIS equivalent models.
3. Obtain the RMSE, ME and SD values comparing the performance of PSO trained LOG10D-ANFIS, LOG10D-ANFIS and ANFIS equivalent models.

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4. Develop a universal model based on the PSO trained LOG10D-ANFIS and the analyzed models.

2 LITERATURE REVIEW

2.1 Introduction

Wireless networking works by sending radio transmissions on specific frequencies where listening devices can receive them. Antennas are also key components of these radio communication systems, picking up incoming signals or radiating outgoing signals [4], [5]. Some antennas, may be mounted externally while others are embedded inside the device's hardware enclosure [2], [6]. Prediction modelling of the received signal strength by these devices is an important concept in the area of wireless communication. Many approaches have been used over the years as seen in [15]-[23]. Despite these models being effective no researcher has taught of developing a universal model.
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 Other models used in wireless signal prediction

COST231 One-Slope Model

This one of the empirical model which 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. It is the simplest approach to signal loss prediction, since it is based only on the distance between the transmitter and the receiver. It does does not take into account the position of obstacles, the influence of which is respected only by the power decay factor of 2. Factor n and the signal loss at a distance d_0 from the transmitter L(d) in equation (1) increases for a more lossy environment [15], [16], [17].

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

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 (m)

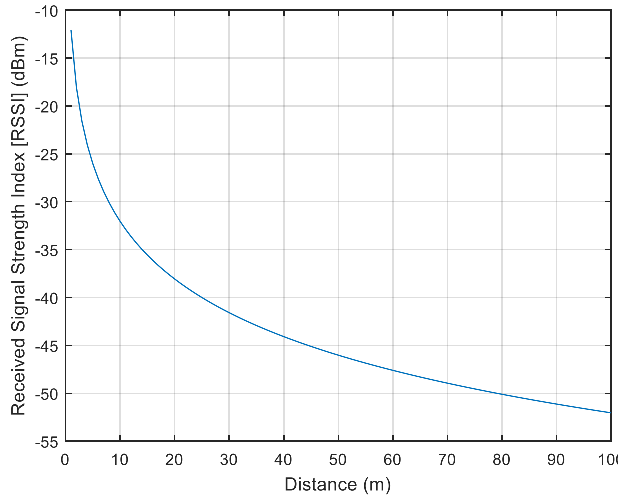

Fig. 1: One Slope Model

Dual-Slope Model

The path loss in dB is given by experimentally.

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

This model divides the distance into two sections. 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:

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

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

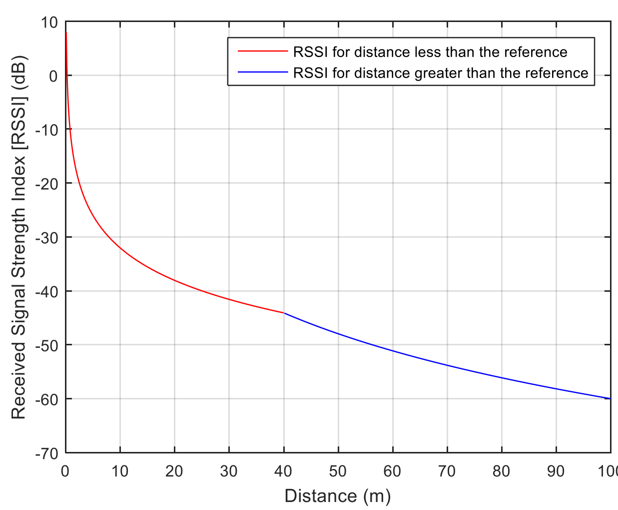

Fig. 2: Dual Slope Model

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Partitioned Model

This model divides the distance into four sections with different loss exponents according to previous field measurement campaigns [15]. The path loss in dB is given by;

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

Average Walls Model

This model is based on the Cost-231 multi-wall where the loss due to obstructing walls is aggregated into just one parameter L. For a single floor environment, the estimated path loss is given by;

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

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:

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

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 must also be taken into account. The loss in dB of the second obstructing wall can be estimated as;

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

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

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

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].

Multi-Wall Model

Due to the inhomogeneous structure of a building with long waveguiding corridors or large open spaces on one side and small complex rooms with many obstacles on the other side, the more accurate, but still partly empirical, Multi Wall model (MWM) employing a site-specific building structure description can be used instead of the OSM.

This model takes into account wall and floor penetration loss factors in addition to the free space loss as given in equation (9). The transmission loss factors of the walls or floors passed by the straight-line joining the two antennas are summed into the total penetration loss L_{Walls} as given in (10) or L (11), respectively. Depending on the wall, either homogenous wall 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 represented as;

$$L_{MWM} = L_1 + 20log_{10}(d) + L_{Walls} + L_{Floors} \quad (9)$$

$$L_{Walls} = \sum_{i=1}^{l} a_{w_i} k_{w_i} \quad (10)$$

$$L_{Walls} = a_f k_f \quad (11)$$

L_{MWM} is the Predicted signal loss (dB)
L_1 is the 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

Its results are more accurate than those of OSM since it considered existing obstales. The computation time of the MWM is 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.

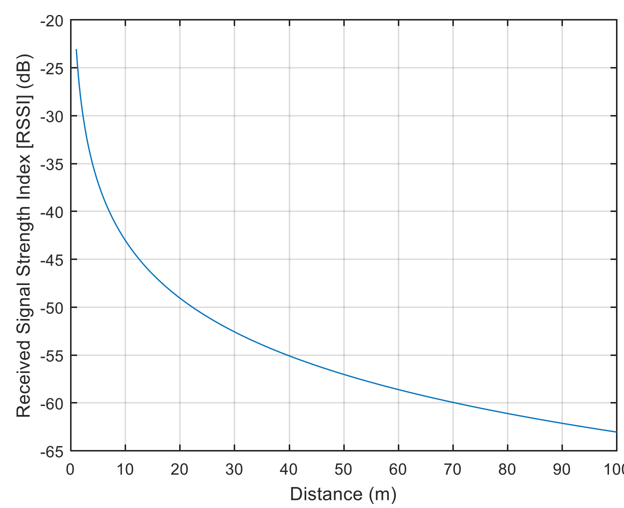

Fig. 3: MW Model

Okumura-Hata model

The *Okumura-Hata model* is based on Okumura's analysis of path-loss characteristics based on a large amount of experi-

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mental data collected around Tokyo, Japan. He selected propagation path conditions and obtained the average path-loss curves under flat urban areas. After which he applied several correction factors for other propagation conditions, such as:

i. Antenna height and carrier frequency
ii. Suburban, quasi-open space, open space, or hilly terrain areas
iii. Diffraction loss due to mountains
iv. Sea or lake areas
v. Road shape

Hata derived empirical formulas for the median path loss to fit Okumura curves as represented in Fig. 4. Hata's equations are classified into three models as given in equation equations (12), (13) and (14) for rural, sub-urban and urban environments respectively.

Urban Area

$$L_{50} = 69.55 + 26.16\log f_c + (44.9 - 6..55\log h_b)\log d - 13.82\log h_b - a(h_m)\ \mathrm{dB} \quad (12)$$

Where:

$a(h_m)$=Correction factor (dB) for mobile antenna height
L_{50} = medium path loss
h_b = base station antenna height
Fc = carrier frequency
h_m = MS antenna height
d = distance between antennas

Sub-urban areas

$$L_{50\ \text{sub urban}} = L_{50\ \text{urban}} - 2\left[\log\left(\frac{F_C}{28}\right)^2 - 5.4\right] \quad (13)$$

Rural

$$L_{50\ \text{rural}} = L_{50\ \text{urban}} - 4.78(\log F_c)^2 + 18.33\log F_c - 40.94\mathrm{dB} \quad (14)$$

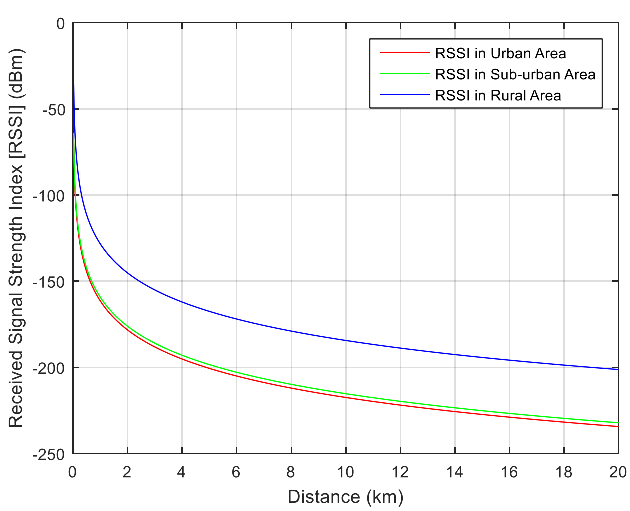

Fig. 4: Hata-Okumura Model

COST-231 Model

COST-231 Model is a combination of empirical and deterministic models for estimating the path loss in an urban area over the frequency range of 800MHz to 2000MHz. The model is used primarily in Europe for the GSM 1800 system. According to [2] it has the following working parameters and mathematical representations.

$L_0 = 4 - 0.114*(\varphi-55);$ (15)
$L_f = 32.4 + 20*\log10(d) + 20*\log10(f_c);$ (16)
$L_{rts} = -16.9 - 10*\log10(W) + 10*\log10(f_c) + 20*\log(d_{hm}) + L_0;$ (17)
$L_{bsh} = -18*\log10(11+d_{hb});$ (18)
$k_d = 18 - 15*d_{hb}/d_{hm};$ (19)
$k_a = 54 - 0.8*h_b;$ (20)
$k_f = 4 + 0.7*((f_c/925)-1);$ (21)
$L_{ms} = L_{bsh} + k_a + k_d*\log10(d) + k_f*\log10(f_c) - 9*\log10(b);$ (22)
$d_{hm} = h_r - h_m;$
$d_{hb} = h_b - h_r;$ (23)
$L_{50} = L_f + L_{rts} + L_{ms}\mathrm{dB}$ (24)

Where:

f_c = carrier frequency
W = street width (m)
b = distance between building along radio path (m)
d= separation between transmitter and receiver (km)
h_r = average building height (m)
h_b = base station antenna height
h_m = MS antenna height
φ = incident angle relative to the street
L_f = Free space path loss = $32.44 + 20\log f_c + 20\log d$
L_{rts} = roof top to street diffraction and scattering losses
L_{ms} = Multiscreen losses

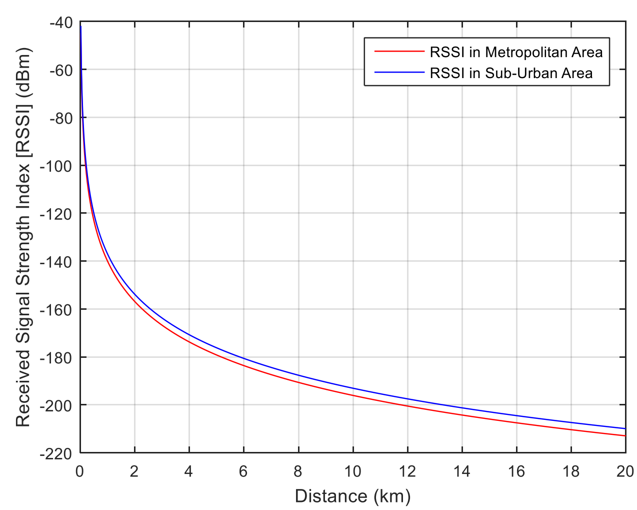

Fig. 5: COST231 Model

COST231-HATA Model

The *COST231-HATA Model* is an improvement Hata model to extend the frequency of operation [2]. The model is used primarily in Europe for the GSM 1800 system [2]. Its equations as

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well as graphical representations are given in equations (25) to (29) and Fig. 6.

ahm1 = (hm*((1.1*(log10(f_c))) - 0.7)) - ((1.56*(log10(f_c))) - 0.8); mobile antenna height correction factor (25)

Metropolitan area

Lcm = 46.3 + (33.9*(log10(f_c))) - (h_b*13.82) - ahm1 + ((44.9-(6.55*(log10(h_b)))).*(log10(d))) + 3; (26)

rLcm = P_t + G_t + G_r - L_{cm}+30;rssi in metropolitan area(27)

Sub-urban area

Lcsu = 46.3 + (33.9*(log10(f_c))) - (h_b*13.82) - ahm1 + ((44.9-(6.55*(log10(h_b)))).*(log10(d))); (28)

rLcsu = Pt + Gt + Gr - Lcsu+30; rssi in sub-urban area (29)

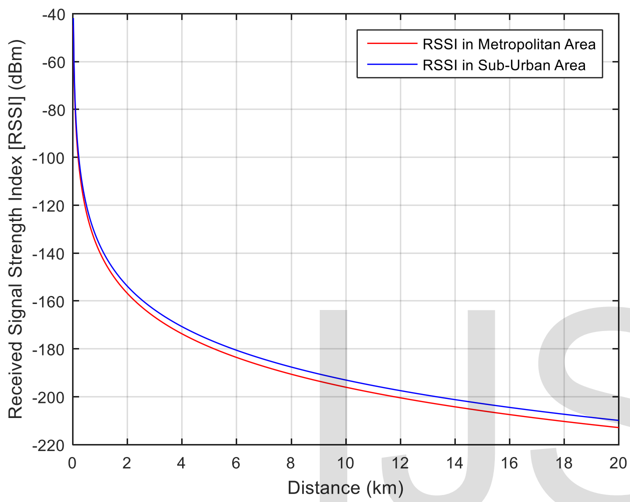

Fig. 6: COST231-Hata Model RSSI versus distance

Artificial Neural Networks

Artificial Neural Network based models use the concept of living organisms' behavior to solve problems [13]. They can be trained to understand a given environment, approximate the relation that can exist between a given input and output and operate based on a number of inputs and one output [18]. The inputs can be in a complex environment where the output is the path loss. This complex environment includes topographical and morphological data in terms of; antenna heights, distance, frequency and obstacles in the indoor and outdoor environments [19]. Because of the several input parameters one might not be able to determine an exact analysis function to transform an input to an output of propagation loss [20]. This led to the development and use of ANN models which are able to learn through training and give a particular output for a given set of inputs. The training is done using different training methods. The actual output is compared to the desired output target and an error determined. The error is reduced to a minimum by changing the weights and biases of a neural network. This is done in the process of training the network. The network performance is based on the mean absolute error, root mean square and standard deviation.

All the models discussed above are not based on any universality which our model is trying to implement. According to [14] and to the best of our knowledge, there is no exixting universal model.

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. 7.

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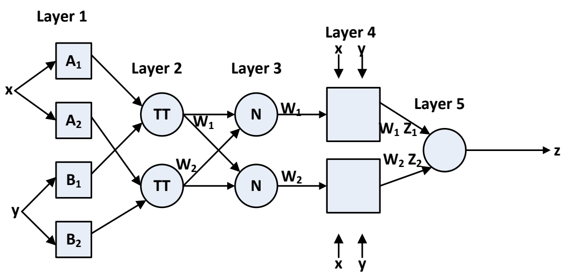

Fig. 7. Type 3 ANFIS Architecture.

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 universal model

In our improved ANFIS, the type 3 ANFIS architecture with one input distance (x) and one output, RSSI (z), is shown in Fig. 8. The input is passed through a logarithmic function before it goes to layer 1 where the premise parameters are modified using PSO. This is to imitate the natural behavior of RSSI with respect to distance based on the inverse square law. In layer 4 where the consequent parameters are modified using PSO, the distance input x is also passed through the logarithmic function.

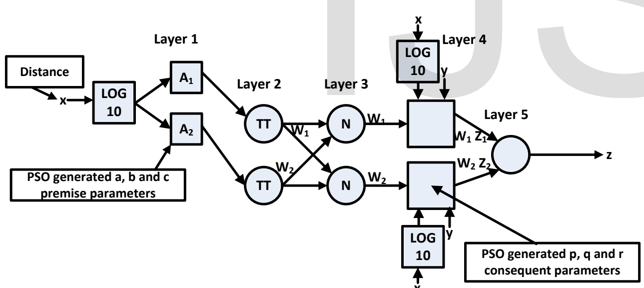

Fig. 8. Modified type 3 ANFIS Architecture.

$Rule\ 1: If\ log10x\ is\ A_1\ then\ z_1 = p_1log10x + r_1$
$Rule\ 2: If\ log10x\ is\ A_2\ then\ z_2 = p_2log10x + r_2$
x=distance and z=rssi

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:

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

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

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:

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

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:

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

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:

$$\overline{w_i}z_i = O_i^4 = \overline{w_i}(p_ix + q_iy + r_i) \quad (33)$$

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:

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

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,

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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 (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.

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

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.

$$xp = xpp + V_i \tag{36}$$

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].

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].

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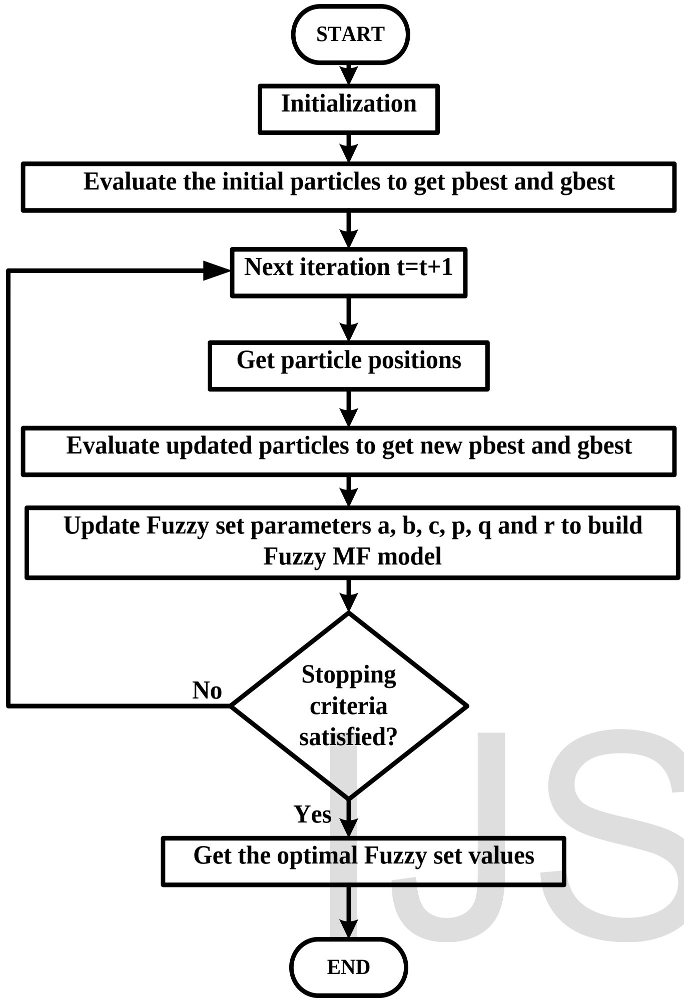

Fig. 9: ANFIS training with PSO flowchart

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):

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

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

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

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

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

Table 1: Training performance comparison of One Slope ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS RSSI prediction models

	RMSE	ME	SD	R^2
ANFIS	0.3180	0.2315	0.2183	0.9983
LOG10D-ANFIS	1.17e-07	7.60e-08	8.84e-08	1
LOG10D-PSO-ANFIS	4.74e-15	2.95e-15	3.70e-15	1

Table 2: Testing performance comparison of One Slope ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS RSSI prediction models

	RMSE	ME	SD	R^2
ANFIS	0.3146	0.2302	0.2148	0.9983
LOG10D-ANFIS	1.16e-07	7.59e-08	8.83e-08	1
LOG10D-PSO-ANFIS	4.72e-15	2.91e-15	3.72e-15	1

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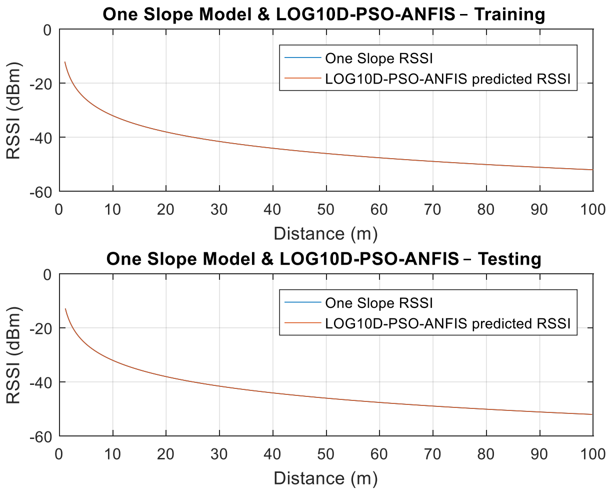

Fig. 10: OSM and LOG10D-ANFIS training and testing

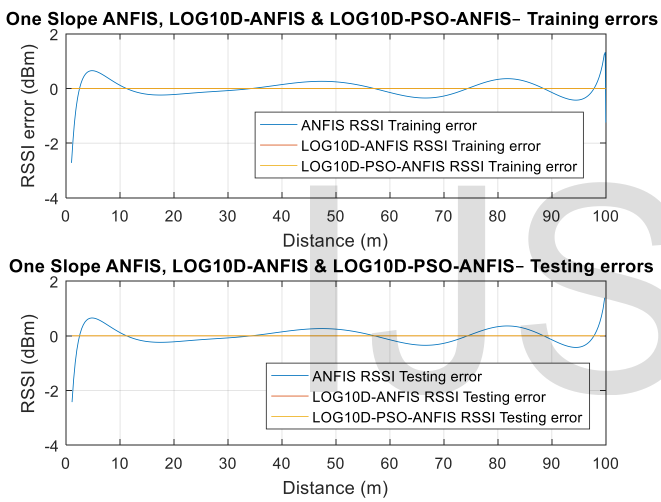

Fig. 11: OSM ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS training and testing errors

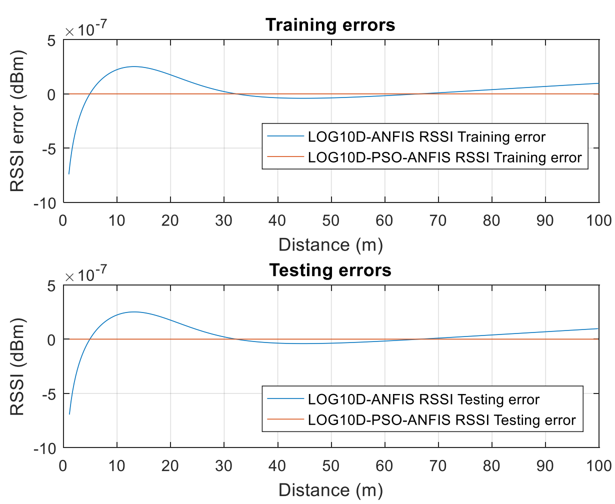

Fig. 12: OSM LOG10D-ANFIS and LOG10D-PSO-ANFIS training and testing errors

Table 3: Training performance comparison of Okumura-Hata Model Rural ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS RSSI prediction models

	RMSE	ME	SD	R^2
ANFIS	1.8957	0.8877	1.6762	0.9938
LOG10D-ANFIS	7.75e-07	5.62e-07	5.34e-07	1
LOG10D-PSO-ANFIS	1.09e-14	4.34e-15	1.00e-14	1

Table 4: Testing performance comparison of Okumura-Hata Model Rural ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS RSSI prediction models

	RMSE	ME	SD	R^2
ANFIS	1.6473	0.8767	1.3967	0.9953
LOG10D-ANFIS	7.75e-07	5.62e-07	5.34e-07	1
LOG10D-PSO-ANFIS	1.01e-14	3.71e-15	9.43e-15	1

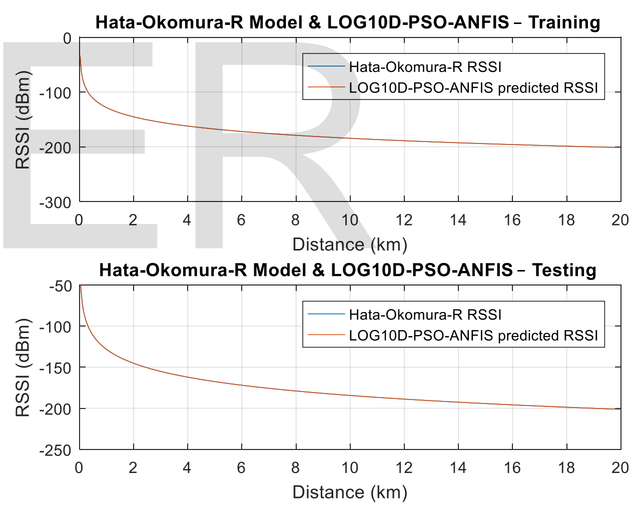

Fig. 13: OSM and LOG10D-ANFIS training and testing

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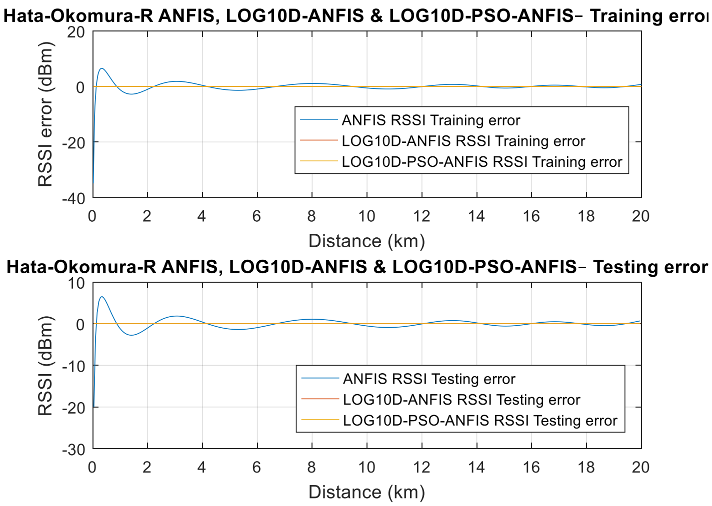

Fig. 14: HORM ANFIS, LOG10D-ANFIS and LOG10D-PSO-ANFIS training and testing errors

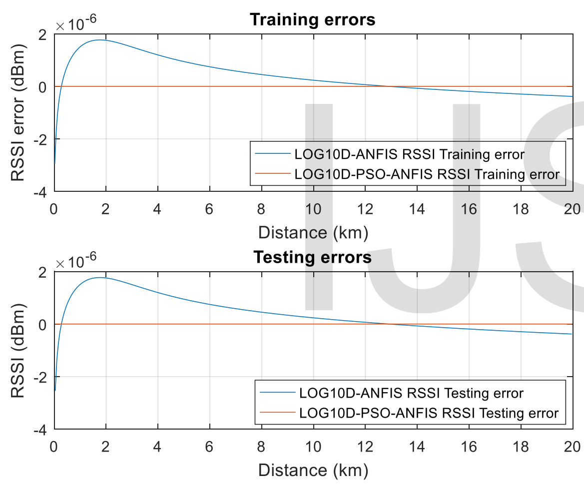

Fig. 15: HORM LOG10D-ANFIS and LOG10D-PSO-ANFIS training and testing errors

Fig. 10 is the training and testing of the predicted signal using PSO trained ANFIS, prediction tool for OSM. The variation is smooth and very close to the calculated values. Fig.s 11 and 12 indicate the training and testing errors variation with distance. The different parameters obtained by comparing the measured and predicted values for the training and testing plots are given in tables 1 and 2. The same analysis is done for Hata-Okumura Rural model and all the other models discussed under literature review where the RMSE values were found to be close to each other in the range of 10^{-15} for the improved ANFIS. Fig.s 13 to 15 and tables 3 and 4 show the performance of Hata-Okumura Rural model.

4.2 The universal model

Based on the results above and the resulting premise and consequent parameters, a universal model is developed. For the OSM and Hata-Okumura Rural model the generated premise and consequent parameters are given in the tables 5 and 6 below. The parameters for all the other models discussed above were also generated with similar results but only the two have been indicated in this paper.

Table 5: One Slope LOG10D-PSO-ANFIS RSSI prediction model premise and consequent parameters after training

	Premise			Consequent	
	a	b	c	p	r
LOG10D -PSO- ANFIS	-30.404	-44.484	-17.151	-39.808	-19.386
	-21.264	-16.437	-23.249	-20.000	-12.044
	-26.643	-33.441	-12.943	-38.469	-22.633

Table 6: Hata-Okumura Rural LOG10D-PSO-ANFIS RSSI prediction model premise and consequent parameters after training

	Premise			Consequent	
	a	b	c	p	r
LOG10D -PSO- ANFIS	-163.79	-60.770	-35.921	-201.00	-100.42
	-136.45	-140.11	-140.25	-56.028	-128.39
	-142.26	-69.099	-55.575	-46.037	-200.77

Using modified ANFIS PSO trained model, the individual membership parameters for each model are obtained through training. Each of the obtained membership parameters, can then be applied to a single ANFIS model depending on the application of the model. Fig. 16 shows a representation of the universal model. The model can be used for all environments and all frequencies.

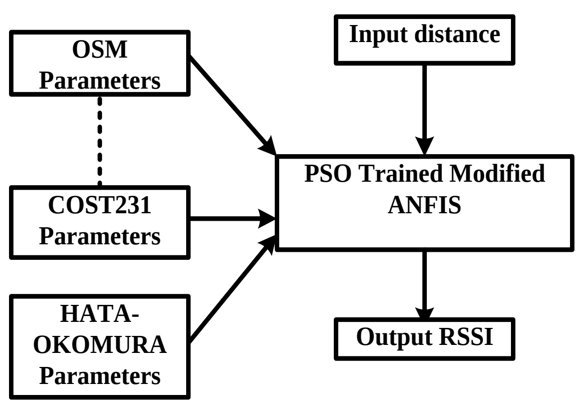

Fig. 16: PSO trained modified ANFIS universal model

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5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

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

The values obtained above indicate the closeness of predicted to the target values indicating that the PSO trained ANFIS is very accurate in approximating the different wireless prediction models. This can be used as a universal theoretical prediction model instead of using the individual models mentioned above.

5.2 Areas of further study

Future research should include the use of different training methods and compare the resulting parameters. Implementation of the model in software as simulator can also be done in future.

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