*International Journal of Engineering & Technology*, 7 (4.10) (2018) 464-469

International Journal of Engineering & Technology

*Website: www.sciencepubco.com/index.php/IJET*

*Research paper*

# Path Loss Model Optimization Using Stochastic Hybrid Genetic Algorithm

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## Abstract

In the context of modeling the propagation of mobile radio signals, optimizing the existing path loss model is largely required to precisely represent the actual propagation medium. In this paper, a hybrid tuning approach is proposed by merging the stochastic Weighted Least Square method and Genetic algorithm. The proposed hybrid optimization is employed to optimize the parameters of Cost 231 Hata propagation model and is validated by cellular field strength measurements at 900 MHz in the sub urban region. The hybrid optimization is compared with optimized results of Weighted Least Square method and Genetic algorithm. The least values of Mean Square error (0.2702), RMSE (0.4798) and percentage Relative error (3.96) justify the tuning precision of the hybrid method. The proposed optimization approach could be used by network service providers to improve the quality of service and in mobile radio network planning of 900 MHz band for 4G LTE services.

***Keywords***: *Cost 231 Hata model; Genetic algorithm; Path Loss; Root Mean Square Error; Weighted Least Square.*

## 1. Introduction

The wireless cellular communication networks are the most widespread networks across the world and have become an integral part of our daily life. The first generation cellular systems introduced in 1987 have been greatly evolved with the improvements in technology. There have been continuous efforts to achieve better data rates and improve the quality of service provided to the users. The coverage limitations in the 3G are overcome and higher speeds are obtained by the use of 4G Long Term Evolution (LTE) advanced network services [1]. Basically 900 MHz is used worldwide for GSM voice and fundamental data communication. The 900 MHz is emerging as the mainstream spectrum choice to be operated as the LTE band, because of its excellent coverage features in rural and sub urban areas and best penetration in the indoor scenarios [2]. The coverage and quality of service could also be improved, by suitable selection of a propagation model and optimizing its parameters to accurately predict the channel behavior prior to the installation of the mobile radio network. The optimized model could be used by network engineers to determine appropriate values for parameters such as base station antenna height, down tilt angle, frequency and transmitted power [3]. Using an optimized model in the design stage would ensure the best performance of the communication system and save the time and cost before the actual system deployment [4].

In the work done earlier, various techniques are presented to optimize the existing mobile radio path loss models. Chhaya Dalela, Prasad and P. K. Dalela used a linear iterative method of least square theory to tune Cost-231 Hata model in different environments [5]. Mousa, Dama, Najjar and Alsayeh performed the optimization using least square method for standard macro cell model and Walfisch-Bertoni model [6]. Joseph and konyeha developed an optimized Hata model for prediction of path loss experienced by CDMA2000 signals in South-Nigeria [7]. Omar Banimelhem et.al presented the optimized Hata model using Genetic algorithm and swarm optimization which was validated by measurements collected from experimental sites [8].

Although various path loss models are developed, they are suited for specific region. It is not possible to have a single formulation to all the models requiring optimization, since the design parameters are different for different scenarios. Moreover, the terrain conditions in which these models are developed largely differ from the Indian region. Hence it is much advantageous to optimize the parameters of propagation model as per the desired environment. The overall objective of model optimization is to minimize the difference to obtain a minimum error between path loss measurements and corresponding model predictions. The propagation model optimization makes the model more precise for received wireless signal strength predictions [3].

In this paper, an effort is made to optimize the parameters of the most commonly used Cost 231 Hata propagation model by combining the Stochastic weighted Least Square method and the conventional Genetic algorithm. The precision of the proposed optimizing approach is improved, since weighted coefficients obtained statistically are used and additionally it includes the advantages of the population based method. The performance is evaluated by comparison with optimization performed by Weighted Least Square method and Genetic algorithm. The proposed hybrid optimization procedure could be used in the implementation of 900 MHZ for 4G LTE, to obtain better signal coverage and good in building penetration.

## 2. Optimization Approaches

A general optimization algorithm is a procedure which is executed iteratively by comparing various solutions till an optimum result is obtained. It is required to create a mathematical model of the optimal design problem [9]. The optimization process begins with the identification of the design variables that vary during the process and setting up various equality and inequality constraints. The statistical optimization approach uses the predictors that are found by statistical analysis and all environmental influences are implicitly taken into consideration [9]. In this approach, the first step is the formulation of a suitable statistical model. Drive tests are performed to collect measurement data of the network. The data is analyzed to identify the errors and is converted into a suitable format to obtain the predictor coefficients. The objective of tuning is to minimize the error between the predictions and measurements [5]. The stochastic processes are generally grouped as Stochastic Calculus methods and Stochastic Evolutionary methods based on the properties. The Stochastic Calculus methods generally involve computations with partial derivatives, Linear Least Square algorithm, and Weighted Least Square algorithm. The Stochastic Evolutionary processes are used to model population in which each individual in a generation produces random number of individuals in next generation to produce an optimized or minimum of the objective function.

The accuracy of the stochastic tuning approach depends on the accuracy of the measurements, and on how well the actual propagation medium is statistically modeled. This method is widely used because of its simplicity and fast calculations. The statistical tuning approach achieves fairly good prediction results when the propagation environment is homogeneous and similar to the environment where the measurements are taken. This section briefly describes the Weighted Least Square method, Genetic algorithm and the hybrid optimization approach which combines the weighted Least Square method and Genetic algorithm implemented on Cost 231 Hata path loss propagation model.

### 2.1. Weighted Least Square Method

The weighted least squares method is an extension of Least Squares method, to obtain parameter estimates which were developed by the mathematicians Karl Friedrich Gauss, Adrien Marie Legendre and Robert Adrain, respectively [10]. This method is used for observations with same responses but unequal variances as compared to the Least Square method which assumes that the measured data has constant variance [10].

In the normal Least Square method the unknown parameters are estimated by minimizing the sum of the squared deviations between the measurements and the model predictions. The least square algorithm is implemented to fit a linear model on data with or without constraints. Mathematically, the deviations between the observed responses and the estimations using the Least Square method is given as [11][12]

$$E(a, b, c, \dots) = \sum_{i=1}^{n} [y_i - f(x_i a, b, c, \dots)]^2 \quad (1)$$

In the context of optimizing the mobile radio propagation model the terms in the above equation can be correlated as

$y_i$ = Measured path loss data at distance $x_i$

f ($x_i$a, b, c…) = Model estimated path loss at distance $x_i$

a, b, c = Parameters of the path loss model required to be optimized

n = number of measured data points

The advantages of a Least Square method include its effectiveness in data utilization and good results can be obtained with small data steps. The disadvantages of a Least Square method are its poor extrapolation properties and its sensitivity to outliers that could alter the results to a large extent.

The fit is improved in the Weighted Least Squares method in which an additional weight factor is included in the fitting process. The error estimate is minimized in the Weighted Least-Squares [11] [13].

$$E(a, b, c, \dots) = \sum_{i=1}^{n} wi[yi - f(x_i\ a, b, c, \dots)]^2 \quad (2)$$

$w_i$ are the weights that have to be statistically estimated. The error function E (a, b, c...) must be minimized which is done by equating all the partial derivatives of the error function to zeros [14].

$$\partial E/\partial a = 0,\ \partial E/\partial b = 0,\ \partial E/\partial c = 0 \quad (3)$$

The sum of the square of residuals is differentiated with each parameter and the coefficients values are obtained by equating the differential solutions with zero. The weights in the weighted Least Square method determine the effect of each response value on the final parameter estimates. Knowing the variances of the measurement errors in the data, the weights are given as

$$w_i = \frac{1}{\sigma i^2} \quad (4)$$

The important aspect in implementing the weighted least Square method is it is based on the assumption that the errors are uncorrelated with each other and the independent variables differ in their variances. To calculate the required weights, the variance of the error residuals is computed and the reciprocal of the variance is taken as the weights. The weights are inversely related to the error variance and a small error variance has large weight with more information and a large error variance has a smaller weight [11].

The weighted least square errors as per Equation 2 are minimized and parameter estimates are obtained. The weights can also be specified in a relative manner, if the variances are not known. The weights could also be based on previous research or the iterations can be repeated till the estimated coefficients stabilize. The minimization performed by weighted least square method improves the fit and gives better results for practical applications compared to the least square method. This method gives more reliable and optimum solution compared to other calculus tuning approaches.

### 2.2. Genetic Algorithm

Genetic Algorithm (GA) was invented by John Holland in the 1960s at the University of Michigan [13]. It is a search technique based on principles inspired from the genetic and evolution mechanisms found in natural systems and populations of living beings. The population evolves over time through competition of survival of the fittest along with controlled variation which includes recombination and mutation [13]. The working of the Genetic algorithm is briefly described as follows [13].

1. An initial population is randomly generated.
2. The algorithm generates a sequence of new population at each step by using the individuals of the current population.
3. The fitness value of each individual in the current population is computed and raw fitness scores are converted into a range of usable values.
4. Based on the fitness values few individuals are selected and named as parents.
5. The individuals in the current population with lower fitness values are passed to the next population.
6. Mutations or crossovers are performed to produce children and the current population is replaced with children to form next generation.
7. The algorithm stops when one of the stopping criteria is met.
   If the specified numbers of generations are reached, time limit exceeds or if the desired fitness level is reached. The algorithm is also stopped when the function tolerance exceeds the average relative change in the fitness function value over the generations.

The individual points completely converge at the last iteration and therefore minimize the objective function. The individuals in the population get closer together with the increasing generations and therefore reach the minimum point.

## 3. Path Loss Model Optimization with Stochastic Hybrid Genetic Algorithm

The optimization techniques provide opportunities for introducing new standards and improve the existing services. The proposed optimization approach merges the weighted Least Square method with the Genetic algorithm.

In this paper, the data collected at 948 MHz downlink frequency across five base stations, located in the sub urban region of Hyderabad city in India is employed for the path loss optimization analysis. The proposed optimization method is implemented on Cost 231 Hata model, since this model was validated as the best suited path loss model for the specified sub urban scenario [14]. The hybrid optimization approach implemented on Cos231 Hata model is described by the flowchart given in Figure 1.

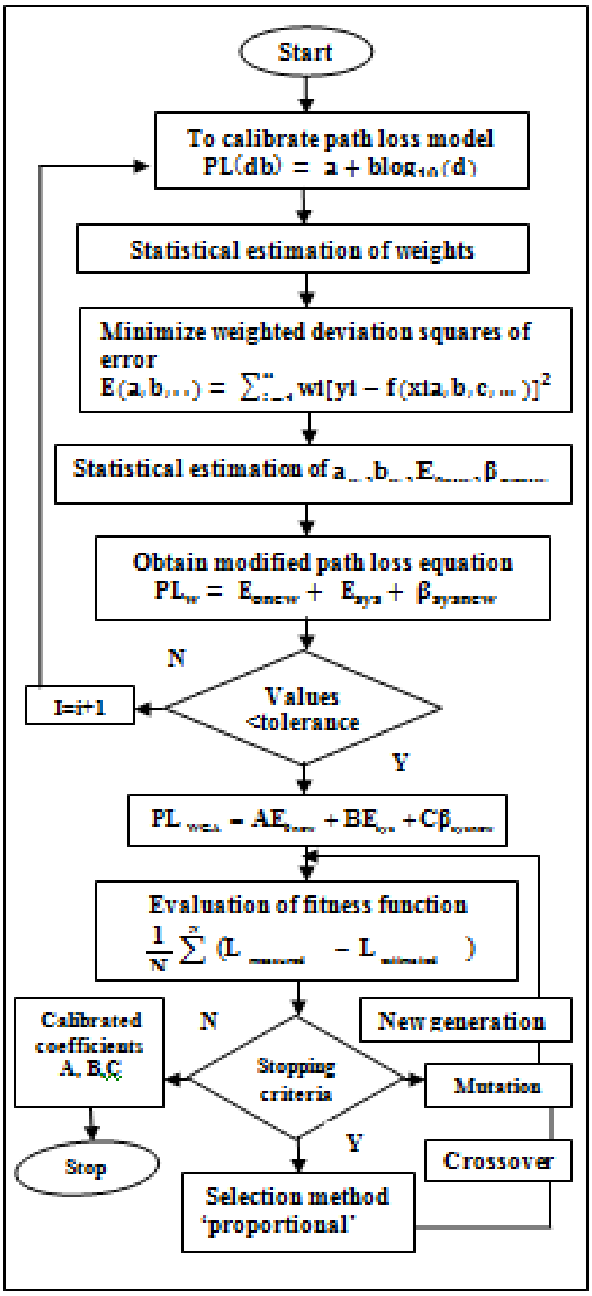


**Fig1:** Stochastic Hybrid Genetic Algorithm

The following are the steps to optimize the Cost 231 Hata Propagation model by the hybrid approach of weighted Least Square method and Genetic algorithm.

**Step1**:

The path loss of Cost-231 Hata model in decibels is given as per Equation 5. This model was developed for use in 1500-2000MHz with mobile antenna heights up to 10m and base station heights of 30-200m [14].

$$PL = 46.3 + 33.9 \log_{10}(f_c) - 13.82 \log_{10}(h_b) - ah_r + [44.9 - 6.55 \log_{10}(h_b)] \log_{10}(d) + c_m \quad (5)$$

$h_r$: Mobile station antenna height (m) (1m to 10m),
d: The transmitter-receiver (T-R) distance (km) (1 to 10km)
$h_b$: Base station antenna height (m) (30m to 200m)
$f_c$ : Carrier frequency (MHz)
$c_m$: Correction parameter, $c_m$(urban) = 3dB,$c_m$ (suburban) = 0dB
The correction parameter $ah_r$ is given by the following equations
$ah_r = 3.2(\log_{10}(11.75\, h_r))^2 - 4.97$ (urban environments)
$ah_r = (1.1 \log_{10} f - 0.7)\, h_r - (1.56 \log_{10} f - 0.8)$ (rural)
$h_r$ : Height of the mobile station antenna (m)
The parameters in Equation 5 are rearranged and the modified Hata model is given as [14]

$$PL(db) = E_0 + E_{sys} + \beta_{sys} \quad (6)$$

Initially the model is first separated into three elements namely initial offset parameter $E_0$ , system design parameter $E_{sys}$, and the slope of model curve $\beta_{sys}$ given as [14].

$$\left.\begin{aligned} E_o &= 46.3 - a_m + c_m \\ E_{sys} &= 33.9 \log_{10}(f_c) - 13.82 \log_{10}(\log_{10}(h_b)) \\ \beta_{sys} &= (44.9 - 6.55(\log_{10}(h_b)) \log_{10}(d) \end{aligned}\right\} \quad (7)$$

**Step 2:** The path loss given in Equation 6 is written as

$$PL(db) = a + b\log_{10}(d) \text{ where } a = Eo + E_{sys} ;\ b = \beta_{sys} \quad (8)$$

PL is the path loss (dB) and both factors (a) and (b) are constant for a given set of measurements.

**Step 3:**

In order to obtain a best fit, the function of sum of deviation squares of the error between the measured path loss and model predicted path loss must be minimized. Applying the weighted Least Square algorithm the error function is given as

$$E(a, b, c \dots) = \sum_{i=1}^{n} W_i [y_i - P_{R,i}(x_i a, b, c, \dots)]^2 = \min \quad (9)$$

$y_i$ = experimentally measured values of path loss at the distance $x_i$;
$P_{R,i}(x_i a, b, c, \dots)$ = model predicted path loss values at distance $x_i$ based on tuning;
a, b, c ,= parameters of the model based on tuning.
n = number of experiment data set.
The error function $E(a, b, c \dots)$ must be least. To ensure this all partial differential of the E function should be equal to zeros.
$\partial E/\partial a = 0$; $\partial E/\partial b = 0$; $\partial E/\partial c = 0$.
Obtaining the solutions to the above equations and by repositioning the elements results in the following expressions

$$n . a_w + b_w \sum x_i = \sum y_i \text{ and } a_w \sum x_i + b_w \sum x_i^2 = \sum (x_i . y_i) \quad (10)$$

The statistical estimates of parameters $a_w$ and $b_w$ are obtained using the weighted Least Square method. In this method it is assumed that the error variances are uncorrelated. The Standard Deviation ($D_i$) of the error between the measured and Cost-231 Hata estimated values are found and the weights are given as$(\frac{1}{{D_i}^2})$. Knowing the weighted statistical estimates $a_w$ and $b_w$ the new values of E0 and $\beta_{sys}$ are given as

$$\left.\begin{aligned} a_w &= \frac{\sum W_i x_i^2 \,.\, \sum W_i y_i - \sum W_i x_i \,.\sum x_i W_i y_i}{n \,.\sum W_i x_i^2 - (\sum W_i\, x_i)^2} \\ b_w &= \frac{n \,.\sum W_i x_i y_i \;- \sum W_i x_i . \sum W_i y_i}{n \,.\sum W_i x_i^2 - (\sum W_i\, x_i)^2} \end{aligned}\right\} \quad (11)$$

$$E_{0\,new} \;=\; a_w - \;E_{sys} \qquad\qquad \beta_{sys\,new} = \frac{b_w}{44.9 - 6.55\,.\log h_b} \quad (12)$$

The new values of $E_{0\,new}$ and $\beta_{sys\,new}$ are re substituted in the rearranged Cost 231 Hata model of Equation 6 and the Path loss modified by Weighted Least Square method is given as

$$PL_w = \;E_{onew} + \;E_{sys} + \;\beta_{sysnew} \quad (13)$$

**Step 4**:
In the next step, the parameters of the Weighted Least Square model are optimized by implementing the Genetic algorithm. The weighted path loss ($PL_w$) in Equation 13 is modified as

$$PL_{(wGA)} \;=\; AE_{onew} + \;B\,E_{sys} + \;C\,\beta_{sysnew} \quad (14)$$

A, B and C are tuning coefficients obtained from the Genetic algorithm.

**Step 5:**
For implementing the Genetic algorithm, a suitable fitness function is formulated which computes the mean of the difference between the estimated and measured path loss values

$$\text{Fitness Function} = \left(\frac{1}{N}\right)\sum_{i=1}^{N}(L_{measured} - L_{estimated}) \quad (15)$$

$L_{measured}$ is the measured path loss, $L_{estimated}$ is the path loss estimated from the optimized weighted least square method and N is the number of observations. In this case, the tuning is achieved by minimizing the difference between the measured path loss and weighted least square optimized path loss values.

**Step 6:**
The steps in the Genetic algorithm to obtain the optimum values of A, B and C for the fitness function are summarized [13]

a. Generate a population of proposed solutions of size n: $S_1$, $S_2$… $S_n$. The initial population in the analysis is composed of 50 individuals, generated in a random manner
b. Calculate the fitness value of each solution: $f(S_1)$,…,$f(S_n)$
c. Select a pair of the current chromosomes for mating by applying the option proportional.
d. Generate two chromosomes by performing a crossover operator with probability $P_c$ between the selected pair, using the 'Two point' function.
e. Perform the mutation operation the two offspring with probability $P_m$.
f. Repeat steps c, d, e until 'n' new chromosomes are generated. The Individuals, generated from these genetic operators, will be included in the new population using the 'elitism insertion' method
g. Finally, a stop test is performed. It verifies if the maximum number of iterations as specified has been exceeded. If the condition is satisfied, the algorithm stops with an optimal solution else it goes to Step b.

The optimized Coefficients A, B and C obtained from the Genetic Algorithm are substituted in Equation 14.

Therefore Cost 231 Hata model optimized by the hybrid approach of Weighted Least Square and Genetic algorithm is given as

$$PL_{(wGA)} \;=\; AE_{onew} + \;B\,E_{sys} + \;C\,\beta_{sysnew} \quad (16)$$

The initial offset parameter( $E_o$) and slope of the model curve ( $\beta_{sys}$) are modified by stochastic Weighted Least Square method and the optimum values A,B and C are obtained using Genetic algorithm. Equation 16 is the proposed optimized Cost 231 Hata empirical path loss model.

## 4. Results and Discussions

In this paper, the cellular received signal strengths are collected experimentally in the vicinity of five base stations in the sub urban region of Osmania University in the Hyderabad city of Southern India. The drive test is done over a distance of 2.5 km, assuming automatic handoff has occurred at successive base stations. The measured signal strengths are pre processed to extract only the large scale fading components which include path loss and shadowing effects. The small scale fading components are filtered out. The mean path loss is computed by averaging the samples in the interval between 10 λ to 40 λ to meet the criteria of estimating the path loss [15].

The equipment used for data collection consists of GSM Wavecom WM01-G900 modem, a Global Positioning System (GPS) receiver ML250, a receiving antenna at a height of 1.5 m and a laptop with a suitable interface [16]. The car with the set up was driven along the sub urban region and received signal strengths were continuously recorded. The Global System for Mobile communications (GSM) and Global Positioning System (GPS) data sheets are suitably obtained for analysis. The information of the locations of base stations and measured received signal strengths is presented in paper [14]. The path loss components from the received signal strengths are extracted knowing the transmitted power, gain of base stations and antenna cable loss. The GPS data sheets are useful to find the distances from the base stations to any point on the route of the drive test. The path loss extracted in decibels from the measured signal strengths is shown as a scatter plot, with respect to the distance as in Figure 2[14].

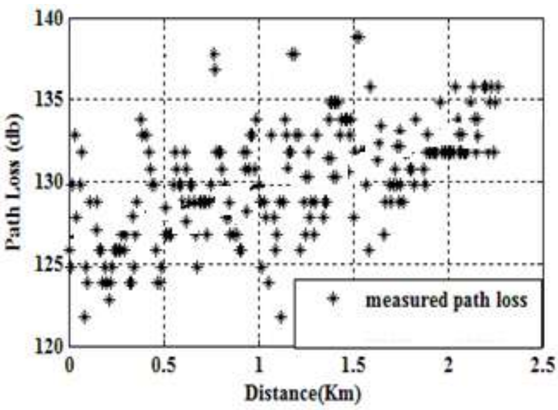


**Fig. 2:** Measured Path loss

The measured path loss is found to have a mean value of 102.14db and a standard deviation of 11.21db. The Least Square method is implemented on the measured path loss and the least square path loss curve obtained is used as a reference for validation. According to this method, the path loss at a given location with respect to path loss at a reference distance $d_0$ is given as [14],

$$PL(d) \;=\; PL(d_o) \;+\; 10n\log 10(d/d_o) + s \quad (17)$$

'n' is the measured path loss exponent obtained from the least square regression of the measured path loss given in Figure 2 and its value is found to be 3.12 . The reference distance do is100 meters, s is the shadow fading factor due to obstacles in the propagation path (8.2 db to10.6 db), and PL ($d_o$) is the free space path loss at reference distance do. The measured path loss is plotted as a least square curve in Fig.3 is taken as a reference for comparison.

### 4.1. Weighted Least Square Optimization of Cost 231 Hata Path Loss Model

Cost 231 Hata path loss model is selected for optimization based on the comparison of path loss exponents. The Path loss exponent predicted by Cost 231 Hata model is found to be 3.56. It has a close agreement with the measured path loss exponent (3.12) compared to the predictions made from other models [14]. Hence Cost 231 Hata model is selected for optimization to further improve the path loss prediction in the specified sub urban scenario.
The Weighted Least Square optimization is implemented on Cost 231 Hata prediction model. The path loss model is optimized statistically by computing the weighted coefficients of the initial offset parameter (Eo) and slope of the model ($\boldsymbol{\beta_{sys}}$) curve to obtain better optimized results. The optimized parameters obtained from weighted Least Square method are summarized in Table 1.

**Table 1:** Weighted Least Square Optimized Parameters

| Parameters | Path Loss models | |
|---|---|---|
| | Cost 231 Hata model | Weighted Least Square Optimized Cost 231 model |
| Initial Offset parameter ( $E_0$) | 46.3 | 32.9201 |
| slope of model curve ($\boldsymbol{\beta_{sys}}$ ) | 0.0170 | 0.0601 |

The modified parameters obtained from the weighted Least Square method are substituted in the original Cost 231 Hata model and the optimized path loss is predicted. The mean path loss is obtained from the modified Cost 231 Hata model using weighted Least Square method is found to be 109.285db. The average path loss using Least Square optimization without weights is found to be 111.11 decibels [14]. The weighted Least Square optimization improves the path loss prediction by 1.825 db compared to the Least Square method, since its mean path loss has a much closer agreement with the measured path loss (102.4 db). The results justify the significance of weighted Least Square method in the context of optimizing the mobile radio path loss model there by providing a more optimum and reliable solution.

### 4.2. Optimization of Cost 231 Hata Path Loss Model by Genetic Algorithm

The Cost-231 Hata model is tuned using the Genetic Algorithm, which is an Evolutionary tuning method. The Genetic Algorithm is implemented using the fitness function which computes the mean of the difference between the estimated and measured path loss values at each evaluation step of the algorithm. The optimized coefficients obtained from the Genetic algorithm are summarized in Table 2. The parameters in Table 3 are used for the operators of Genetic Algorithm.

**Table 2:** Optimized Coefficients from Genetic Algorithm

| Optimized coefficients of Cost 231 Hata model | | |
|---|---|---|
| A | B | C |
| 0.7702 | 0.7303 | 0.7577 |

**Table 3:** Values of operators for Genetic Algorithm

| Operator Name | Value |
|---|---|
| Population Size (N) | 50 |
| Number of Iterations | 60 |
| Crossover ($P_c$) | 1 |
| Mutation ($P_m$) | 1 |

The coefficients A, B and C are substituted for the respective parameters of initial offset (Eo), system design parameter ($E_{sys}$), and the slope of model curve ($\beta_{sys}$) to obtain the path loss optimized by Genetic algorithm. The mean path loss obtained from this method is found to be 96.96 db. The Genetic algorithm has a better performance compared to the weighted Least Square method. It provides a path loss improvement of 1.445 db compared to the optimization by Weighted Least Square method.

### 4.3. Optimization of Cost 231 Hata Path Loss Model by Proposed Stochastic Hybrid Genetic Algorithm

In the hybrid optimization approach, the weighted Least Square optimized Cost 231 Hata path loss model is further optimized using Genetic algorithm. The statistical precision of the coefficient estimates is further fined tuned by population based approach of Genetic algorithm. The optimized coefficients obtained from Genetic algorithm for the hybrid approach is summarized in Table 4.

**Table 4:** Optimized Coefficients from Hybrid Genetic Algorithm

| Optimized coefficients of Cost 231 Hata model | | |
|---|---|---|
| A | B | C |
| 0.5745 | 0.9091 | 0.9105 |

The Cost-231 Hata path loss model optimized by weighted stochastic Genetic algorithm is given by substituting the coefficients A, B and C as

$$PL_{(WGA)} = (0.5745)E_{onew} + (0.9091)E_{sys} + (0.9105)\,\beta_{sysnew}$$

An overall comparison of the optimization techniques is made in terms of path loss as given in the comparison graph of Figure 3.

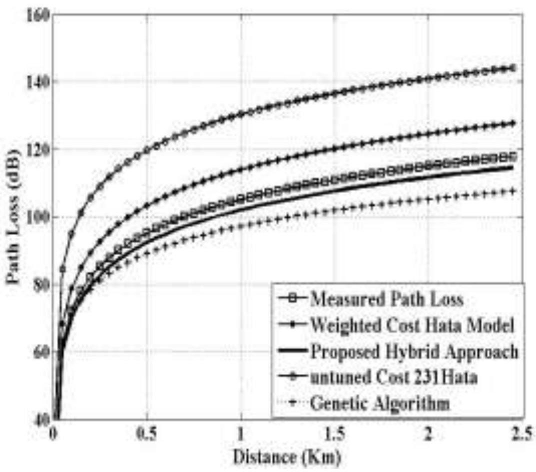

**Fig.3:** Optimized Path Loss Comparison

The performance of the Optimization methods is evaluated in terms of path loss and error metrics as per Table 5 and Table 6.

**Table 5:** Optimized Path Loss Comparison

| Path Loss (db) | Measured Path Loss | Cost 231 Hata model | Optimization Methods | | |
|---|---|---|---|---|---|
| | | | Weighted Least Square | Genetic algorithm | Hybrid Approach |
| Min | 5.99 | 23.96 | 7.579 | 16.55 | 5.137 |
| Max | 117.8 | 144 | 127.6 | 107.5 | 114.4 |
| Mean | 102.4 | 127.6 | 109.2 | 96.96 | 99.36 |

**Table 6:** Comparison of Optimization methods in terms of Error Metrics

| Error Metrics | WeightedLeast Square | Genetic Algorithm | Hybrid Approach |
|---|---|---|---|
| MSE | 2.1304 | 1.9184 | 0.2702 |
| RMSE | 1.4596 | 1.3851 | 0.4798 |
| Std of Error | 1.4304 | 1.4128 | 0.4702 |
| %Relative Error | 9.60 | 7.67 | 3.96 |

From the results of Table 5, it is observed that the optimization methods improve the performance of the path loss model. The average path loss predicted from the proposed hybrid optimization method has a best agreement with the measured path loss. The mean path loss predicted by the Weighted Least Square method differs from the measured path loss by 6.885 db, where as for the Genetic algorithm it differs by 5.44db. The Genetic algorithm has a better performance compared to the weighted Least Square method. The path loss difference is the least for the hybrid optimization approach (3.04 db), since this method merges the advantages of stochastic method and the evolutionary algorithm to provide the best path loss performance.

The error metrics in Table 6 are least for the optimization performed by the hybrid approach. The path loss and error metric results suggest the effectiveness of the proposed stochastic hybrid Genetic algorithm for optimizing the path loss model as compared to the existing methods.

The proposed optimization method is validated for mobile signal measurements at 900 MHz. Although higher speeds are obtained for 4G services, but the features of excellent coverage and indoor penetration are retained by employing 900 MHz band. The proposed hybrid optimization approach is aimed to have improved path loss estimation. The proposed model can be effectively used in the link budget design of 4G LTE networks employing 900 M Hz band.

## 5. Conclusion

Path loss model optimization is a major requirement in the design and implementation phase of mobile radio networks. In this paper, a stochastic hybrid Genetic Algorithm is proposed for the optimization of mobile radio path loss model. The hybrid optimization approach combines the statistical analysis of weighted Least Square method and evolutionary technique of Genetic algorithm. The optimization methods are implemented on Cost 231 Hata path loss model. The performance is evaluated in terms of path loss comparison and error metrics. The optimization performed by the hybrid method produces least MSE (0.2702) and RMSE (0.4798), thereby justifying its precision in tuning the path loss model. The validations are performed with mobile radio measurements at 900 MHz, and therefore the proposed optimization approach could be satisfactorily used for 4G LTE systems deployed on 900 MHz to provide better coverage in sub urban and rural areas.

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