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Path Loss Models Optimization for Mobile Communication in Different Areas

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Abstract
In mobile radio systems, path loss models are necessary for proper planning, interference estimations, frequencies assignments and cell parameters which are basic for network planning process. Empirical models are the most adjustable models that can be suited to different types of environments. In this paper, data collected in Batna, Algeria is used to calculate the path loss for GSM (908-957 MHz). The measured path loss is compared with theoretical path loss estimated by the most widely empirical models «Cost123», «Hata», «SUI» and «Egli». The best model to estimate the measured path loss is optimized using genetic algorithm to predict path loss for suburban and rural area. The RMSE and the other test criteria between the actual and predicted data are calculated for various path loss models. It turned out that the adjusted COST 231 model outperforms the other studied models. The investigated results can help telecommunication engineers improve their planning and design of microcellular system.

Keywords*: GSM, path loss, empirical models, genetic algorithm*

1. Introduction:

Accurate estimation of propagation path loss is a key factor for the good design of mobile systems. Such needs are of a great concern of mobile system designers to optimize system parameters such as number and locations of transmitters, power coverage and interference level. Accurate prediction methods are needed in order to determine these parameters of a radio system that will increase the efficiency of service quality, reduce undesirable power losses, increase coverage area, and determine best base stations arrangements of a specified area [1, 2].

Since the terrain conditions vary to a large extent, the path loss prediction models cannot be generalized. This drawback can be overcome by adjusting the model parameters to suit the desired environment [3].

In the last few years, many researchers have applied different algorithms to predict the path loss in theirs environments [4-6]. However, optimized model can provide optimal parameters for radio-wave path-loss predicting in the target area. This is the main issue discussed in this paper in which, we are interested in the most widely used empirical propagation models such as «Cost231», «Hata», «SUI» and «Egli» based on different parameters such as frequency, distance, antenna height [7, 8]. Because of this we use genetic algorithms since they are non-deterministic, and this component of chance can be configured by modifying several parameters, such as the mutation rate.

For this exploration we presented a program that uses genetic algorithms to optimize the appropriate empirical model and make it more appropriate to the desired area coverage with the objective of finding the global minimum of a cost function test. All the particular characteristics of the genetic algorithm, including the global minimum making it worth for using it to solve such a problem; optimization makes it the best tool for such a crucial issue from the idea of finding the global minimum of a cost function in a direction to minimize the mean square error between the prediction data set by this optimized model and real measure established from the field of study.

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The rest of this paper is organized as follows. In section 2 and 3 we review each empirical models and Experimental setup. Section 3 presents the application, results and discussion. Finally, in the last section we present our conclusion and potential future work.

2. Path Loss Model

In wireless channels, the path loss prediction is very important factor that enables planning the effective transmitted power, coverage area and quality of service. However, several global and local parameters will affect path-loss prediction model. Empirical models describe from a statistical point of view the relationship between the path loss and the environment. Results are usually obtained by means of measurement campaigns.

In this paper, we have considered four various Empirical models for our study as follows:

2.1. Egli Model

Egli prediction model is an empirical model which has been proposed by [9]. The Egli model is a simplistic model to approach radio-wave path-loss of irregular topography. Based on real data the path-loss approaching can be formulated as following:

$$\mathrm{PL} = 20\log(\mathrm{f_c}) + 40\log(\mathrm{d}) - 20\log(\mathrm{h_{te}}) + \begin{cases} 76.3 - 10\log(\mathrm{h_{re}}), & \mathrm{h_{re}} \leq 10\mathrm{m} \\ 85.9 - 20\log(\mathrm{h_{re}}), & \mathrm{h_{re}} \geq 10\mathrm{m} \end{cases} \quad (1)$$

where

h_{te}= height of the base station antenna. Unit: meter (m)

h_{re}= height of the mobile station antenna. Unit: meter (m)

d = distance from base station antenna. Unit: meter (km)

f = frequency of transmission. Unit: megahertz (MHz)

2.2. Hata's Model

Basically, this model has been introduced to urban areas; and with some correction factors it could be extended to suburban and rural areas. For urban area the median path loss equation is given by

$$\mathrm{PL(urban)(dB)} = 69.55 + 26.16\log(\mathrm{fc}) - 13.82\log(\mathrm{h_{re}}) - \mathrm{a}(\mathrm{h_{re}}) + (44.9 - \log(\mathrm{h_{te}}))\log \mathrm{d} \quad (2)$$

For suburban area, it is expressed as

$$\mathrm{PL(suburban)(dB)} = \mathrm{PL(urban)} - 2[\log(\mathrm{fc}/28)]2 - 5.4 \quad (3)$$

Finally, for open rural area, it is modified as:

$$\mathrm{PL(open)(dB)} = \mathrm{PL(urban)} - 4.78(\log(\mathrm{fc}))2 + 18.33\log(\mathrm{fc}) - 40.94 \quad (4)$$

The correction factor, ($\mathrm{a}(\mathrm{h_{re}})$), in Equation (2), differs as a function of the size of the coverage area.

For small and medium areas, it is:

$$\mathrm{a}(\mathrm{h_{re}}) = (1.1\log(\mathrm{fc}) - 0.7)\mathrm{h_{re}} - (1.56\log\mathrm{fc} - 0.8)\mathrm{dB} \quad (5)$$

For large area, it is:

$$\mathrm{a}(\mathrm{h_{re}}) = 8.29(\log 1.54\mathrm{h_{re}})2 - 1.1\mathrm{dB} \text{ for fc} < 300\mathrm{MHz} \quad (6a)$$

$$\mathrm{a}(\mathrm{h_{re}}) = 3.2(\log 11.75\mathrm{h_{re}})2 - 4.97\mathrm{dB} \text{ for fc} > 300\mathrm{MHz} \quad (6b)$$

In the above equations, d is the transmitter-receiver antenna separation distance and it is valid for 1km–20km, fc represents the operating frequency from150 MHz to 1500 MHz. The transmit antenna height, h_{re}, ranges from 30m to 200m and the receive antenna height, h_{re}, ranges from 1m to 10m are considered [10].

2.3. Cost 231 Hata Model

The COST 231 model, sometimes called the Hata model PCS extension, is an improved version of the Hata model. It is widely used for predicting path loss in mobile wireless system.

It is designed to be used in the frequency band from 1500 MHz to 2000 MHz. It also includes corrections for urban, suburban and rural (flat) environments [10].

$$\mathrm{PL(d)(dB)} = 46.3 + 33.9\log(f_c) - 13.82\log(h_{te}) - a(h_{re}) + (44.9 - 6.55\log(h_{te}))\log(d) + C_M \quad (7)$$

And C_M=0 dB for medium sized city and suburban area with moderate tree city or C_M =3 dB for metropolitan centers. Validity range of this model is:

$$1500\text{ MHz} < f < 2000\text{ MHz}, 30\text{ m} < h_{te} < 200\text{ m}, 1\text{ m} < h_{re} < 10\text{ m}, 1\text{ km} < d < 20\text{ km}.$$

2.4. SUI Model

In this model, the BS antenna height can be varied from 10 m to 80 m and receiver end the height can vary between 2 m to 20 m . Innovation of this model is the introduction of the path loss exponent ɣ, and the weak fading standard deviation, S, as random variables obtained through a statistical procedure. The value of standard deviation of S is typically 8.2 to 10.6 dB [11].

SUI model comes out with three different types of terrain like terrain A dense urban locality, terrain B has hilly regions and terrain C for rural with moderate vegetation. The general path loss expression according to the SUI model is given by [12].

$$\mathrm{PL} = A + 10\gamma\log_{10}\left(\frac{d}{d_0}\right) + X_f + X_h + s; \quad (8)$$

Where $d > d_0$ (d in meters) is the distance between the base station and the receiving antenna, d_0=100 m, X_f is a correction for frequency above 2 GHz, X_h is a correction for the receiver antenna height, and s is a correction for shadowing because of trees and other clutters on a propagation path. Parameter A is defined as follows:

$$A = 20\log\left(\frac{4\pi d_0}{\lambda}\right) \quad (9)$$

Where λ is the wavelength in meters. Path loss exponent γ given by [13].

$$\gamma = a - b.h_{te} + {}^{c}/_{h_{te}} \quad (10)$$

Where h_{te} is the base station antenna height in meters, and a, b and c are constants dependent on the terrain type, as given in Table 1.

Table 1. Model Parameters for Different Terrains

Model Parameter	Terrain A	Terrain B	Terrain C
a	4.6	4.0	3.6
b (m-1)	0.0075	0.0065	0.005
c (m)	12.6	17.5	20

The correction factors for the operating frequency and for the receiver antenna height for the model are:

$$X_f = 6.0\log\left(\frac{f_c}{2000}\right) \quad (11)$$

And, for terrain typ.

$$X_h = -10.8 \log\left(\frac{h_{re}}{2000}\right); \qquad \text{for terrain type A\&B} \tag{12}$$

$$X_h = -20 \log\left(\frac{h_{re}}{2000}\right); \qquad \text{for terrain type C} \tag{13}$$

Where f, is the frequency in MHz, and h_{re} is the receiver antenna height in meters. The SUI model is used for path loss prediction in rural, suburban and urban environments.

3. Experimental Setup

The Batna city (Algerian) was selected to obtain the measurements. The drive test experimental was made (by a BSS engineer at National mobile operator "Mobilis Batna") in a radius of 1 km for BTS1 covering a small rural area crossing a road in the village 6 km from the city center of Batna, alongside BTS2 covering the area with a radius of 2.5 km, the propagation medium around this region is classified as a suburban area, it is assumed that an automatic handover occurs to adjacent base stations, when the signal strength is low. The emission sites specifications of these bases and their positions are shown in Table 2.

Data were collected when driving a vehicle, having the experimental configuration. It consists of a Special Mobile Phone (Huawei U6100) GPS receiver (NMEA), a receiving antenna, and a laptop with a key and a drive test software (Huawei GENEX Probe). The vehicle was driven within the base station coverage area while continuously recording the received signal. At every moment of the collected measurements, GPS data is also recorded simultaneously.

The information of the base station such that the frequency of transmission or reception, transmitted power and antenna heights are obtained from the operator "Mobilis" of the Batna city for analysis. With the help of GPS data, and the location of base stations, the radial distances from the base station at any point along the route can be calculated.

Table 2. BTS Parameters

Parameters		BTS1	BTS2
Region type		Rural	Suburbain
Transmit power (dBm)		46	43
Cable Loss + Body loss		10.5	9.7
Transmitting antenna gain (dBi)		17.5	16.7
Receive antenna gain (dBi)		0	0
Transmit antenna height (m)		25	35
Mobile station antenna height (m)		1.5	1.5
Operating frequencies (MHz)	Uplink frequency	908	912,4
	Dn-link frequency	953	957,4
Geographic coordinates	Latitude	35,2524	35,62437
	Longitude	6,13074	6,36984

4. Results and Discussion

4.1. Comparison with Prediction Models

To investigate the prediction models, a comparison between predicted path loss and measured path loss have been performed for two base stations BTS1 and BTS2. The performance of the empirical models is then compared to the measured path loss data as in Figure 1 and 2. The values of Mean Error-ME; Root Mean Square Error-RMSE; Standard deviation of error-SE; Relative Error Percentage-(%), are used to measure the forecasting accuracy of these models, are tabulated in Table 3.

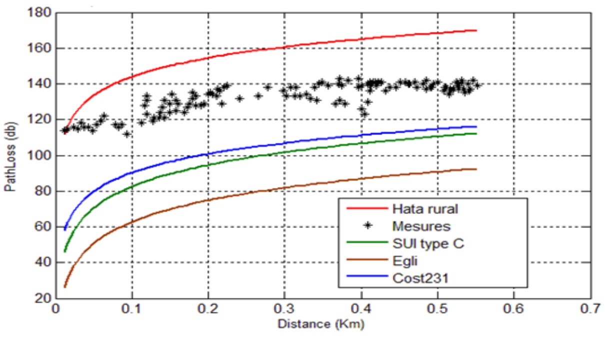

Figure 1. Comparison between Predicted and Measured Path Loss for BTS1

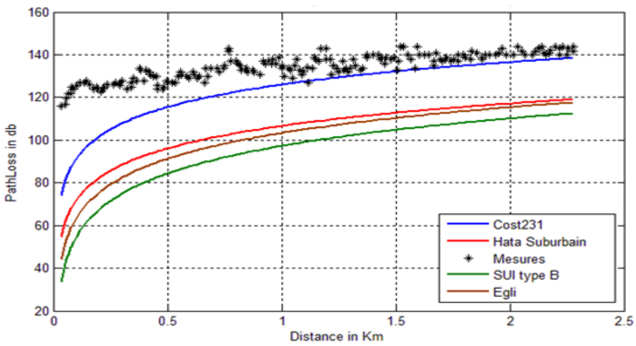

Figure 2. Comparison between Predicted and Measured Path Loss for BTS2

From Table 3, few points can be drawn. It is found that performance of the COST231 Hata model is the best as RMSE and SE are the lowest compared to other models. Hata model, SUI model and Egli model are overestimating the path loss for both coverage areas in the GSM900 system. Figure 1 and 2 consolidate the result that COST231 Hata model is closet to measured path loss than other models.

Table 3. Performance Comparison between Models used According to Test Criteria

Base Station		**Cost 231**				**Hata**		
	ME	RMSE	SE	(%)	ME	RMSE	SE	(%)
BTS1	26.3666	27.2553	1.4578	20.1037	26.9721	27.8197	1.5036	20.2868
BTS2	10.8454	13.7572	0.6308	8.3029	30.2093	31.3761	1.5296	22.7732
Base Station		**SUI**				**Egli**		
	ME	RMSE	SE	(%)	ME	RMSE	SE	(%)
BTS1	32.5823	33.8035	2.0376	24.9176	50.6938	51.3455	3.5560	38.5894
BTS2	40.1866	41.7637	2.2965	30.3244	33.9151	35.4640	1.8385	25.6050

For both open area and suburban environments, the path loss exponent estimated by the COST-231 Hata model is in closest agreement with the measured path loss (Table 3), which shows the actual path loss characteristics in Batna. Based on this, the COST-231 Hata model is selected as the best model for optimization to develop a new model for the path loss prediction in Batna for GSM 900 system. The next section of the paper describes how the COST-231 Hata model is first optimized by GA to match the measured path loss and then a comparison analysis of the performance of the new optimized model is made against the measured path loss and the path loss estimated by the COST-231 Hata model.

4.2. Optimization Process by GA

The COST 231 model is chosen for this study. Formulating the problem to be solved as a single mathematical equation (chromosome) has five variables (genes) Equation 15, must be defined in a manner make this a suitable model with actual field measurements, assessed by a cost function to a stopping criteria depends on the performance thereof. And this cost function is generally defined as the RMSE (Root Mean Square Error). In order to obtain the best performing genes, a comprehensive solution is also validated by a comparison between this model and others based on actual data to test the applicability in reality.

COST 231(rural/sub) model is defined as:

$$\begin{aligned} &PL = 46.3 + 33.9\log(f_c) - 13.82\log(h_{te}) - a(h_{re}) + (44.9 - 6.55\log(h_{te}))\log(d) + C_M \\ &a(h_{re}) = (1.1\log(f_c) - 0.7)h_{re} - (1.56\log(f_c) - 0.8) \\ &C_M = 0 \end{aligned} \tag{14}$$

It can be written as follows:

$$\begin{aligned} &PL = 46.3 + 44.9\log(d) - 13.82\log(h_{te}) - 6.55\log(h_{te})\log(d) \\ &+33.9\log(f_c) - a(h_{re}) \end{aligned} \tag{15}$$

Table 4. The Optimized Parameters as a Chromosome

K1=46.3	K2=44.9	K3=-13.82	K4=-6.55	K5=33.9

This chromosome is evaluated according to an optimization flowchart defined as follows:

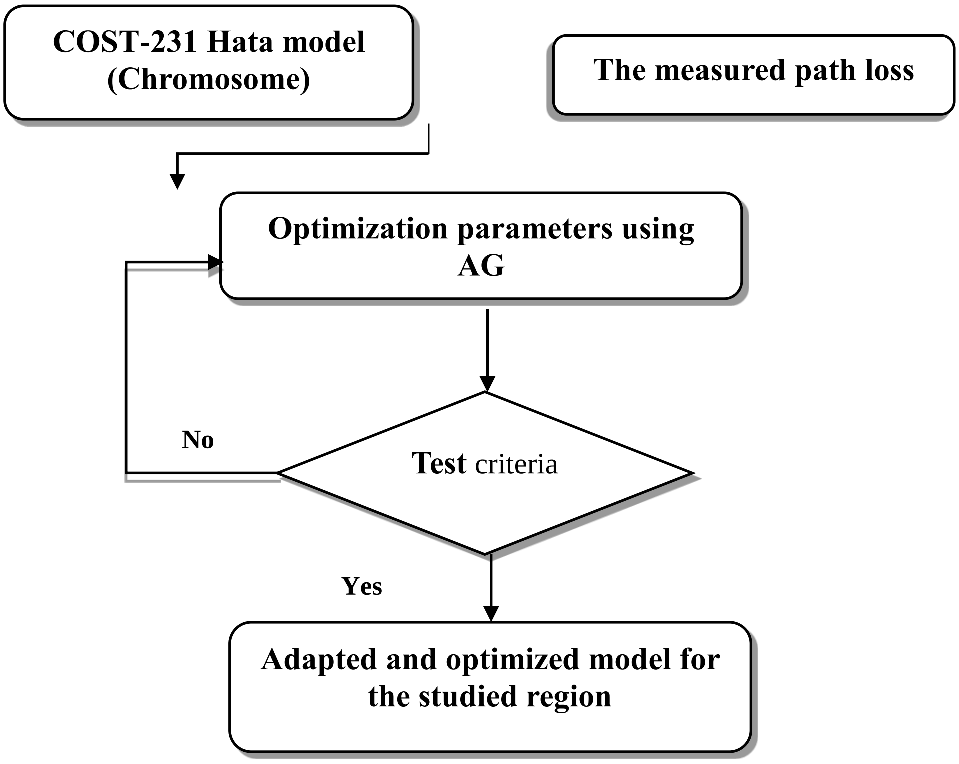

Figure 3. Flow Chart of the Optimization Process

The fitness function f used for the chromosomes evaluation and parameters adjustment is defined by the mean square error (RMSE) as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} |PL_{m,i} - PL_{,i}|^2}{n}} \quad (16)$$

Where PL_m represents the measured path loss in dB, PL is the predicted path loss in dB, and n is the number of the measured data points.

Our goal is to minimize the fitness function (minimizing RMSE) to obtain the best solution (best chromosome) in the population to ensure the accuracy and precision of studied model (COST231). For the implementation of the GA technique, selected parameters are listed in Table 5.

Table 5. GA Parameters used

GA parameters	Values
The population size	20
Maximum generations number	100
Fitness function type	Top
Selection	Stochastic Uniform
Crossover	Heuristic (Crossover rate = 1.5)
Mutation	Adaptive feasible

4.2.1. Optimization Results by GA

Simulation results using the GA parameters are presented in the following tables and figures

Table 6. Results of the Optimization Process for COST-231 Hata Model (rural)

COST231-Opt	Test n°1	Test n°2	Test n°3	Test n°4	Test n°5	COST231	
Parameters 1	13.5659	17.6035	19.0089	13.2472	17.4122	46.3	K1
2	8.7093	4.0752	5.7402	6.8085	7.3201	44.9	K2
3	22.5427	23.0858	20.2126	22.4703	24.3536	-13.82	K3
4	3.0475	3.5723	3.3992	3.7016	5.5924	-6.55	K4
5	32.4942	30.0833	30.4848	31.9975	30.2434	33.9	K5
RMSE	5.0286	5.8339	5.4327	5.0332	4.1420	27.2553	RMSE
Calculating Time (s)	8.959825	8.701118	8.751138	8.645315	8.592212	/	/
N generation	100	100	100	100	100	/	/

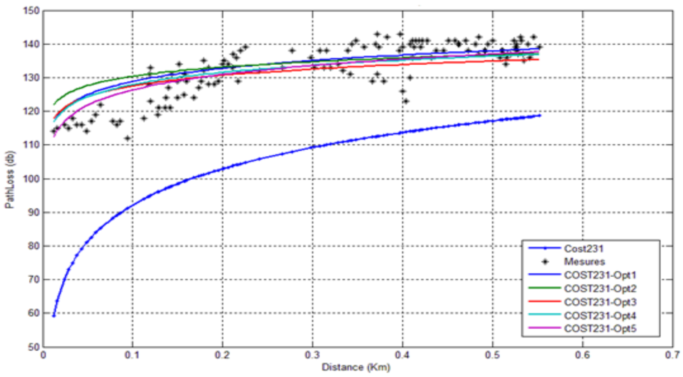

Figure 4. Comparison between COST-231 Hata and COST231-Opt 1,2,3,4,5 (BTS1).

Note that the best model is optimized COST-Opt5 and will be validated later with the other models (rural).

Table 7. Results of the Optimization Process for COST-231 Hata Model (suburban)

COST231-Opt	Test n°1	Test n°2	Test n°3	Test n°4	Test n°5	COST231	
Parameters 1	13.9698	13.8386	20.1981	20.3864	19.1589	46.3	K1
2	7.3151	6.0975	2.1382	4.1111	10.9898	44.9	K2
3	22.2411	27.5947	21.9237	22.5506	24.5060	-13.82	K3
4	4.0101	4.2079	6.9594	6.6409	4.2315	-6.55	K4
5	29.1406	26.4024	27.2499	26.7082	26.3678	33.9	K5
RMSE	3.0385	3.0849	3.0682	3.0647	3.2997	13.7572	RMSE
Calculating Time (s)	9.311313	9.259242	9.201156	9.30156	9.247135	/	/
N generation	100	100	100	100	100	/	/

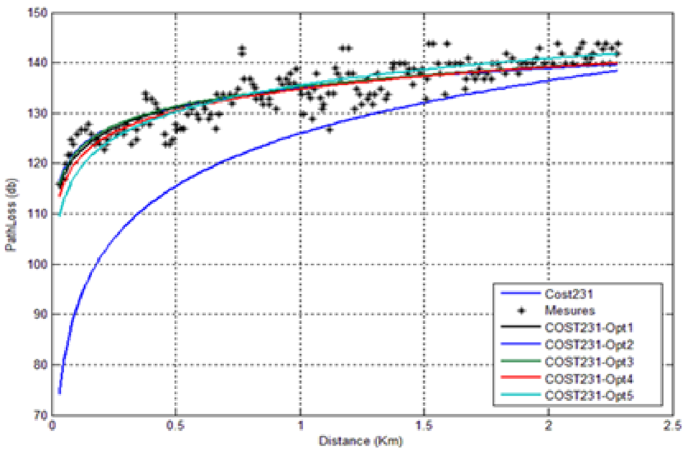

Figure 5. Comparison between COST-231 Hata and COST-231-Opt 1,2,3,4,5 (BTS2).

From the results obtained and observed in Table (7) and Figure (5), the best model is optimized COST-Opt1.

4.2.2. Validation

Table 8. Performance comparison according to the test criteria with COST231-Opts (5.1)

Base Station	**Cost 231**				
	ME	RMSE	SE	(%)	
BTS1	26.3666	27.2553	1.4578	20.1037	
BTS2	10.8454	13.7572	0.6308	8.3029	
Base Station	**Cost 231-Opt 5**				
	ME	RMSE	SE	(%)	COST231-Opt 5 (BTS1) is chosen for comparison.
BTS1	3.6547	4.1420	0.7308	2.8039	
Base	**Cost 231-Opt 1**				

Station	ME	RMSE	SE	(%)	COST231-Opt 1 (BTS2) is chosen for comparison.
BTS2	2.4210	3.0385	0.6855	1.8127	

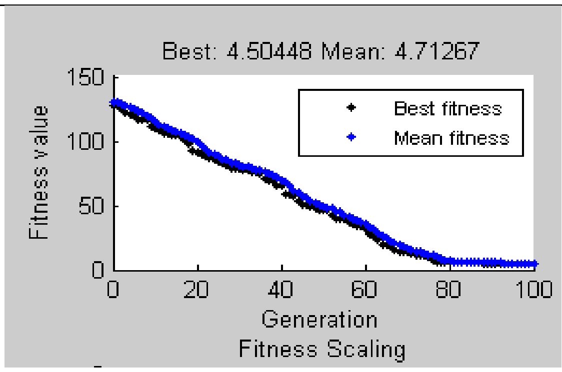

Figure 6. Fitness Function Evolution Versus Number of Generations

Beginning with the results of Table 8, we have noticed that both optimized models COST-Opt5 (rural) and COST-Opt1 (Suburban) surpass cos231 model in terms of overall performance. But the convergence of these two models after the optimization is defined by the stop criterion "Maximum generation number." (100 generations) Figure (6).

5. Conclusion

This paper shows the applicability and efficiency of GA in reconfiguring the distribution system to get minimum losses. Four empirical path loss models namely, the Hata model, the Stanford University Interim (SUI) model, the COST-231 Hata model and Egli model have been investigated.

The path loss data were measured at two plain rural and suburban locations in Batna, Algeria. The measured path loss was compared with that predicted by models. The COST-231 Hata model prediction is found close to measured data in all areas. Distribution systems loss minimum re-configuration methodology using genetic algorithm was proposed. GA was able to produce a near optimal solution by adopting the adaptive nature of natural genetics. From the numerical example, new values of parameters are proposed for COST-231 Hata model based on measured data. It is obvious that adjusted COST-231 Hata model shows the closest agreement with the measurement result. Hence COST-231 Hata model with proposed modification is recommended for rural and suburban area of Batna.

For future work, forecasting other environments (Urban area) of path-loss data by a GA-related model is a challenging issue for study.

References

[1] Bhuvaneshwari A, Hemalatha R, Satyasavithri T. *Statistical Tuning of the Best suited Prediction Model for Measurements made in Hyderabad City of Southern India*. Proceedings of the World Congress on Engineering and Computer Science. San Francisco. 2013; 2.

[2] Torres J, Guardado JL, Rivas-Dávalos F, Maximov S, Melgoza E. A genetic algorithm based on the edge window decoder technique to optimize power distribution systems reconfiguration. *Electrical Power and Energy Systems*. 2013; 45: 28-34.

[3] Tahcfulloh S, Riskayadi E. Optimized Suitable Propagation Model for GSM 900 Path Loss Prediction.*TELKOMNIKA Indonesian Journal of Electrical Engineering.* 2015; 14(1): 154-162.

[4] Surajudeen Bakinde N, Faruk N, Ayeni A, Muhammad M, Gumel M. Comparison of Propagation Models for GSM 1800 and WCDMA Systems in Selected Urban Areas of Nigeria. *International Journal of Applied Information Systems (IJAIS)*. 2012; 2(7): 6-13.

[5] Julie C, Onuu M, Ushie J, Usibe B. Propagation Models for GSM 900 and 1800 MHz for Port Harcourt and Enugu, Nigeria. *Network and Communication Technologies*. 2013; 2(2).

[6] Isabona J, Konyeha C. Urban Area Path loss Propagation Prediction and Optimization Using Hata Model at 800MHz. *IOSR Journal of Applied Physics* (IOSR-JAP). 2013; 3: 8-18.

[7] Imran I, Mustafa S, Mahmood AK, Shahzad A Malik, Shahid A. Path Loss Modeling of WLAN and WiMAX Systems. *International Journal of Electrical and Computer Engineering (IJECE).* 2015; 5: 1083-1091.
[8] Famoriji J, Olasoji Y. Radio Frequency Propagation Mechanisms and Empirical Models for Hilly Areas. *International Journal of Electrical and Computer Engineering (IJECE)*. 2013; 3(3): 372-376.
[9] Egli JJ. *Radio propagation above 40 Mc over irregular terrain.* Proc. IRE. 1957; 45(10): 1383-1391.
[10] Tapan KS, K Zhong Ji, Kyungjung K, Medour A, Salazar M. A survey of various propagation models for mobile communication. *IEEE Antennas and Propagation Magazine*. 2003; 45(3): 51-82.
[11] Azubogu ACO, et al. Empirical-Statistical Propagation Pathloss Model for Suburban environment of Nigeria at 800MHz band. *The IUP Journal of Science and Technology*. India. 2010.
[12] Parsons JD. The Mobile Radio Propagation Channel. 2nd ed. West Sussex: Wiley. 2000.
[13] Erceg V, Greenstein LJ. An empirically based path loss model for wireless channels in suburban environments. *IEEE Journal on Selected Areas of Communications.*1999; 17: 1205–1211.