

# Optimization of Suitable Propagation Model for Mobile Communication in Different Area

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**Abstract**—In this paper, the most widely used empirical path loss models are compared to real data; the most appropriate one (COST-231) has been optimized using three different algorithms to fit measured data for mobile communication system. The performance of the adjusted Cost-231 model obtained by the proposed methods is then compared to the experimental data. The concert criteria selected for the comparison of various empirical path loss models is the Root Mean Square Error (RMSE). From numerical simulations, it was noticed a significant improvement in the prediction made by the proposed algorithm with a slight superiority of Invasive weed Optimization algorithm in term of lower RMSE value in one hand and in term of convergence speed on the other hand compared to PSO and ABC algorithm.

**Index Terms**— Empirical models, Mobil communication, Path Loss, COST-231, Invasive weed Optimization.

## I. INTRODUCTION

The need for connectivity anywhere, added to the increment in the number of users, has caused the development of various generations of mobile communication standards in the last decades. The demand for greater traffic capacity involving both voice and data transmission requires the planning of mobile communication networks comprised of smaller and smaller cells, thus making the number of base stations grow exponentially, and complicating the process of optimizing the location of these stations. Because of this, accurate prediction models are needed for making received signal level/path loss predictions prior to actual network deployment.

In telecommunication industry, path loss is the reduction in power density of an electromagnetic wave signal as it propagates from the transmitter to the receiver [1].

During the planning stage of cellular networks, models are employed to predict the behavioral characteristics of signals using similar attributes and constraints of the environment before deployment. Traditional path-loss prediction model mainly used experimental models such as Egli 1, SUI models, which briefly be introduced in the section 2. The problem of these models is that expressions are based on the qualitative propagation environments such as urban, suburban and open areas. However, in practice, empirical path loss model tuning is usually required due to significant drop in prediction performance of empirical models when applied in the environments other than the ones they are designed.

In the last few years, many researchers have applied different algorithms to predict the path loss in theirs environments [2-6]. To this effect, we need to optimize empirical models to provide optimal parameters for radio-wave path-loss prediction in the target area and have good cellular palanification [7-9].

In this paper, we analyze the performance achievable with intermediate techniques, between purely empirical models and real measure established from the field of study, based on the use of Invasive weed Optimization, particle swarm optimization and artificial bee colony algorithm. First of all the most widely used empirical path loss models: «Cost-231», «Hata», «SUI» and «Egli» are compared to real data; the most appropriate one is then optimized. This technique is employed to curb the problem observed in the differences between the used empirical models and the actual measured data in a particular environment [10].

This latter is the main issue discussed in this paper in which, the performance of the adjusted Cost-231 model obtained by the proposed methods is then compared to the experimental data. The concert criteria selected for the comparison of various empirical path loss models is the Root Mean Square Error (RMSE). From numerical simulations, it was noticed a significant improvement in the prediction made by the proposed algorithm with a slight superiority of IWO algorithm in term of lower RMSE value in one hand and in term of convergence speed on the other hand compared to PSO and ABC method and

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to the genetic algorithm and Nelder-Mead method proposed in [5] and [6] respectively.

The rest of this paper is organized as follows. In section 2 we review the empirical models and the proposed algorithms. Methodology and application are presented in section 3. In section 4 presents the results and discussion. Finally, our conclusion and potential future work are presented in section 5.

## II. DATA OF PROBLEM TO BE SOLVED

### A. Optimization Algorithm

In this paper, to solve the path loss problem, the Invasive weed Optimization, particle swarm optimization algorithm and the artificial bee colony method are considered to minimize the difference between the used empirical models and the actual measured data.

#### 1) Artificial bees colony Algorithm

ABC algorithm is a heuristic optimization algorithm introduced by Karaboga (Karaboga, 2005) inspired from how honey bees work together for collecting nectar from flowers. In ABC, the objective is to find the patch of flowers with maximum nectar amount (optimal solution). For achieving this, the bees are subdivided into three categories such as employed, onlooker and scout bees. Each one represents a D-dimensional solution, the bee which finds the best food source among all is most likely to be followed by other bees for converging to the best location. The aim of employed bees is to exploit the nectar sources explored before and share the information with the waiting bees (onlooker bees) in the hive. This information are related to the quality of food source sites exploited by the employed bees, based on this information, the onlooker bees inside the hive decide on the food source to exploit. The goal of the scout bees is to search randomly around the hive in order to find a new food source site [8].

In ABC algorithm the number of employed bee and onlooker bee is equal to the number of solutions in the population. The artificial bee colony algorithm consists of four main phases. Initial phase, employed bee phase, onlooker bee phase and scout bee phase.

To sum up, the ABC utilizes the concept of memory for storing personal best location. A bee visits randomly a new location and later it compares with the best location that it visited previously. If the new location is better, the old one is forgotten and the new location is memorized; otherwise, the memory remains unchanged. The basic steps of the

ABC algorithm are summarized and depicted via flowchart given in Fig. 1 [11-12]:

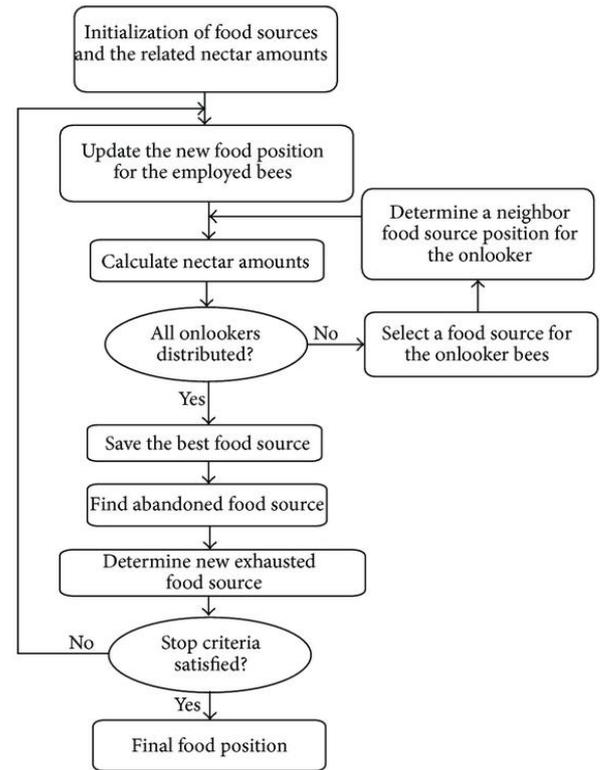


Fig. 1: ABC algorithm flowchart

#### 2) Particle Swarm Optimization

The Particle swarm optimization is a population-based algorithm for searching global optimization problems introduced by Kennedy and Eberhart in 1995 [13]. It has the capability to find global optimal points by using the social interaction of unsophisticated agents. PSO utilizes a population (called swarm) of particles in the search space. The status of each particle is characterized according to its position and velocity.

$$\vec{x}_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{id})$$

and

$$\vec{v}_i = (v_{i1}, v_{i2}, v_{i3}, \dots, v_{id}).$$

To discover the optimal solution, each particle changes its searching direction according to two factors: the best position of a given particle  $x_{li}$  and the best position (global best)  $x_g$  of the entire swarm. PSO searches for the optimal solution by updating the velocity and position of each particle according to the following equations:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (1)$$

The velocity updates are calculated as a linear combination of position and velocity vectors

$$v_i(t+1) = wv_i(t) + C_1\rho_1(x_{li}(t) - x_i(t)) + C_2\rho_2(x_g(t) - x_i(t)) \quad (2)$$

Where  $t$  denotes the iteration in the evolutionary space.  $w$  is the inertia weight.  $C_1$  and  $C_2$  are personal and social learning factors.  $\rho_1$  and  $\rho_2$  are random values uniformly distributed within the range  $[0, 1]$ .

The basic process of the PSO algorithm is carried out with four basic operations: initialization, constraint handling, actualization, evaluation and selection [13]. Figure 2 shows its flowchart.

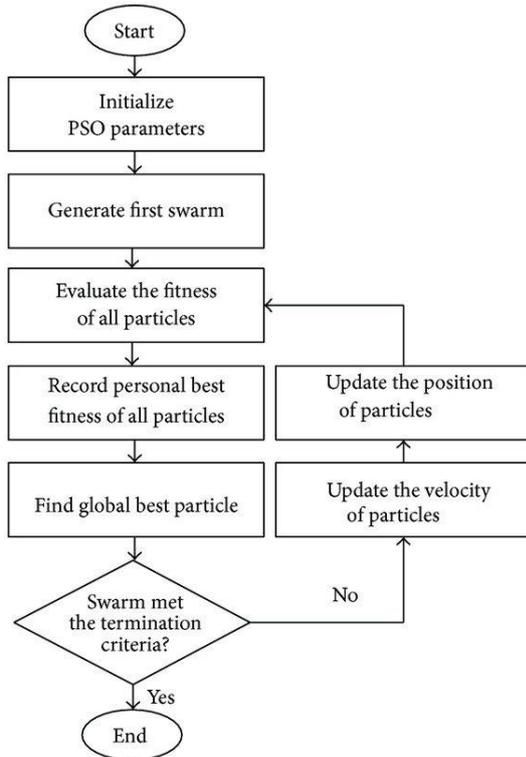


Fig. 2: PSO algorithm flowchart

### 3) The Invasive weed Optimization

The Invasive weed Optimization is a stochastic optimization algorithm which inspired from weed colonization. Weeds have shown to be very robust and can quickly adapt to any environment. Thus, capturing their properties lead to a powerful optimization algorithm [14]. Some of the distinctive properties of IWO in comparison with other evolutionary algorithms are the way of reproduction, spatial dispersal, and competitive exclusion [15].

Considering an  $N$  variable optimization problem, the IWO process begins with initializing a population. That is, a population of initial solutions is randomly generated over the solution space. In optimization problems, seeds and field represent randomly generated initial solutions and  $N$  dimensional problem space, respectively. The fitness of each seed is calculated based on a predefined objective function of the problem. In other words, the number of seeds for each member varies linearly between  $S_{min}$  for the worst member

and  $S_{max}$  for the best member. In the next step for implementing IWO, These seeds are then randomly scattered over the search space by normally distributed random numbers with mean equal to zero and varying standard deviation. The standard deviation is started from a predefined initial value ( $\sigma_{initial}$ ) and reduced to a final value ( $\sigma_{final}$ ) and calculated based on

$$\sigma_{iter} = \left(1 - \left(\frac{iter}{iter_{max}}\right)^n\right) (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \quad (3)$$

where  $iter_{max}$  is the maximum number of iterations,  $\sigma_{iter}$  is the SD at the current iteration and  $n$  is the nonlinear modulation index. The produced seeds, accompanied by their parents are considered as the potential solutions for the next generation.

Once all seeds found their positions and the new plants grew to the flowering plants, they are ranked together with their parents. Some of the existing plants are then removed based on a competitive exclusion process, and an elimination mechanism is adopted such that plants with better ranking have more chance to survive.

This process is continued until the convergence criteria are met. A flow chart describing the IWO algorithm is presented in Fig. 3

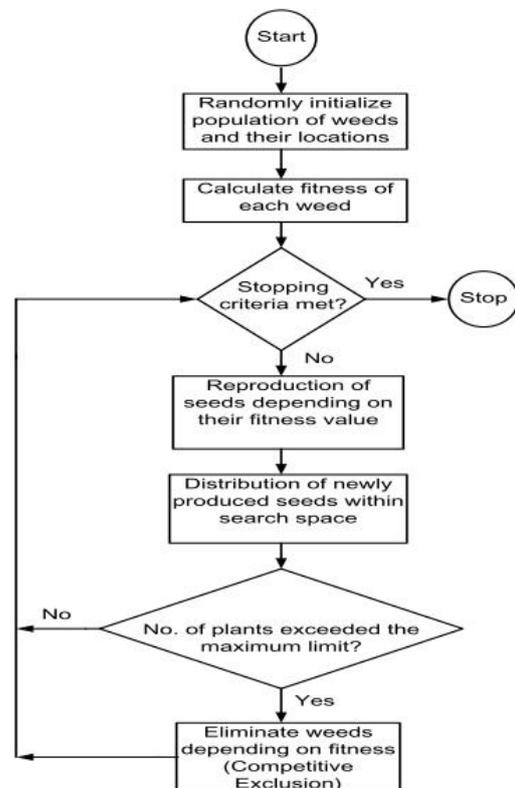


Fig. 3: Invasive Weed Optimization algorithm flowchart

## B. Path loss Models

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:

### 1) Egli Model

Egli prediction model is an empirical model which has been proposed by [16]. Based on real data the path-loss approaching can be formulated as following:

$$PL = 20 \log(f_c) + 40 \log(d) - 20 \log(h_{te}) + \begin{cases} 76.3 - 10 \log(h_{re}), & h_{re} \leq 10m \\ 85.9 - 20 \log(h_{re}), & h_{re} \geq 10m \end{cases} \quad (4)$$

where

$h_{te}$  = height of the base station antenna (m).

$h_{re}$  = height of the mobile station antenna (m).

$d$  = distance from base station antenna (km).

$f$  = frequency of transmission (MHz).

### 2) Okumura Hata 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

$$PL(urb)(dB) = 69.55 + 26.16 \log(f_c) - 13.82 \log(h_{re}) - a(h_{re}) + (44.9 - \log(h_{te})) \log d \quad (5)$$

For suburban area, it is expressed as

$$PL(suburban)(dB) = PL(urban) - 2[\log(fc/28)]^2 - 5.4 \quad (6)$$

Finally, for open rural area, it is modified as

$$PL(open)(dB) = PL(urban) - 4.78(\log(fc))^2 + 18.33 \log(fc) - 40.94 \quad (7)$$

The correction factor,  $a(h_{re})$ , in Equation (5), differs as a function of the size of the coverage area.

For small and medium areas, it is

$$a(h_{re}) = (1.1 \log(fc) - 0.7)h_{re} - (1.56 \log fc - 0.8)dB \quad (8)$$

For large area, it is

$$a(h_{re}) = 8.29(\log 1.54 h_{re})^2 - 1.1dB \quad (9a)$$

$$a(h_{re}) = 3.2(\log 11.75 h_{re})^2 - 4.97dB \quad (9b)$$

In the above equations,  $d$  is the transmitter-receiver antenna separation distance and it is valid for this range 1km–20km,  $f_c$  represents the operating frequency from 150 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 [17,18].

### 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 [19][20].

$$PL(d)(dB) = 46.3 + 33.9 \log(f_c) - 13.82 \log(h_{te}) - a(h_{re}) + (44.9 - 6.55 \log(h_{te})) \log(d) + C_M \quad (10)$$

Where  $C_M$  is a corrective term,  $C_M=0$  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:

$$1500 \text{ MHz} < f < 2000 \text{ MHz},$$

$$30 \text{ m} < h_{te} < 200 \text{ m},$$

$$1 \text{ m} < h_{re} < 10 \text{ m}, \quad 1 \text{ km} < d < 20 \text{ km}.$$

### 4) SUI Model

The IEEE 802.16 wireless network standards consortium group proposed some standards for the frequency range below 11 GHz, having the channel model developed by Stanford University, or SUI model. This model takes the legacy of Hata model's frequency extension for more than 1800 MHz. Little bit of correction in parameters, can be extended up to 3 GHz band frequency.

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 20m [21]-[22]. Innovation of this model is the introduction of the path loss exponent  $\gamma$ , 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 [23].

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 [24]

$$PL(dB) = A + 10\gamma \log_{10} \left( \frac{d}{d_0} \right) + X_f + X_h + s \quad (11)$$

where  $d > d_0$  ( $d$  in meters) is the distance between the base station and the receiving antenna,  $d_0=100m$ ,  $X_f$  is a correction for frequency above 2GHz,  $X_h$  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

$$A = 20 \log \left( \frac{4\pi d_0}{\lambda} \right) \quad (12)$$

where  $\lambda$  is the wavelength in meters. Path loss exponent  $\gamma$  given by [25]

$$\gamma = a - b \cdot h_{te} + c/h_{te} \quad (13)$$

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.

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

$$X_f = 6.0 \log \left( \frac{f_c}{2000} \right) \quad (14)$$

and, for terrain type A and B;

$$X_h = -10.8 \log \left( \frac{h_{re}}{2000} \right); \quad (15)$$

For terrain type C;

$$X_h = -20 \log \left( \frac{h_{re}}{2000} \right) \quad (16)$$

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.

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

### III. EXPERIMENTAL SETUP

The Batna city (Algeria) was selected to obtain the measurements. The drive test experimental was made 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 car, 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. Fig.4 and 5 show the measured signal strength and coverage of GSM network for the two BTS respectively. At every moment of the collected measurements, GPS data is also recorded simultaneously.

The information of the base station such as 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	Suburban
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
	Downlink frequency	953	957,4
Geographic coordinates (°)	Latitude	35,2524 °N	35,62437 °N
	Longitude	6,13074 °E	6,36984 °E



Fig.4. Reception quality and coverage for BTS1



Fig.5. Reception quality and coverage for BTS2

#### IV. RESULTS AND DISCUSSION

##### A. Comparison with Prediction Models

To investigate the prediction process, a comparison between predicted and measured path loss models have been performed for two base stations BTS1 and BTS2. The values of the predicted and the measured path loss are plotted against the separation distance between the Base Station (BS) antenna and the Mobile Station (MS) antenna (Figures 6 and 7). The values of Root Mean Square Error (RMSE), that are used to measure the forecasting accuracy of these models, are tabulated in Table 3.

TABLE 3. PERFORMANCE COMPARISON BETWEEN USED MODELS ACCORDING TO THE TEST CRITERIA

Base station	Cost-231	Hatas	Sui (c/b)	Egli
BTS1	27.2553	27.8197	33.8035	51.3455
BTS2	14.2664	29.1958	39.6199	33.4455

From Table 3, it is found that the performance of the COST 231 Hata model is the best one as the RMSE is the lowest value compared to other models. Figure 6 and 7 consolidate the result that COST 231 Hata model is the closest one to the measured path loss. Based on this observation, the COST 231 Hata model is selected as the best model for optimization process to develop a new model for the path loss prediction in Batna city for GSM 900 system.

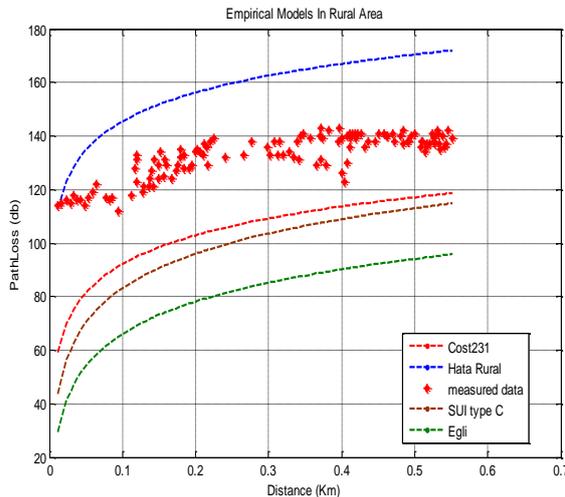


Fig.6. Comparison between predicted and measured path loss for BTS1

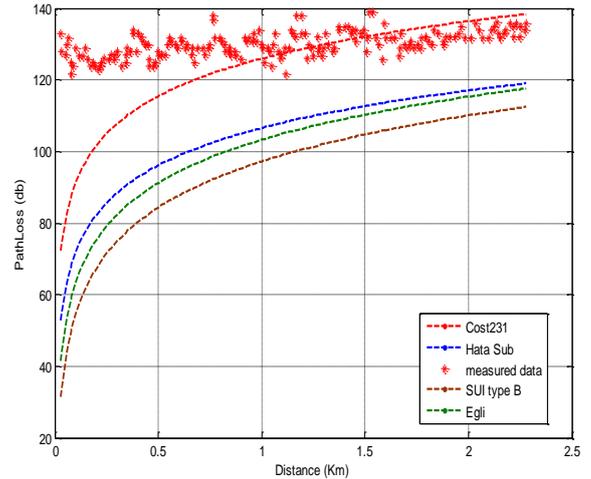


Fig.7. Comparison between predicted and measured path loss for BTS2.

##### B. Optimization Process

In this study, the problem to be solved is formulated as a single mathematical equation that has five variables. Equation (17) must be defined in a manner make it a suitable model with actual field measurements, assessed by a cost function to a stopping criteria depends on the desired performance (Figure 8). This cost function is generally defined as the RMSE (Root Mean Square Error).

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

$$PL = 46.3 + 44.9 \log(d) - 13.82 \log(h_{te}) - 6.55 \log(h_{te}) \log(d) + 33.9 \log(f_c) - a(h_{re}) \quad (17)$$

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

$$RMSE = \sqrt{\frac{\sum_{i=1}^n |PL_{m,i} - PL_i|^2}{n}} \quad (18)$$

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.

Path loss model optimization is a process in which a theoretical propagation model is adjusted with the help of measured values obtained from test field data. The aim is to get the predicted field strength as close as possible to the measured field strength.

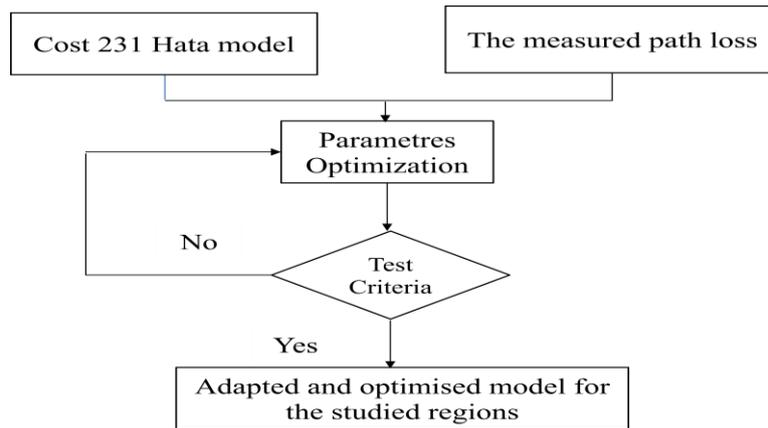


Fig 8. Flow chart of the optimization process

### C. Optimization results

Simulation results are presented in the following tables and figures in which table 4 and 5 show predicted path loss values for existing models, measured data and optimized data of the BTS1 and BTS2 respectively . Fig 9 illustrated a comparative plot of optimized models, Cost 231 model and measured data for the BTS1 while Fig. 10 showed a plot comparing the optimized models with Cost 231 model and measured data for the BTS2.

TABLE 4: PATH LOSS VALUES FOR EXISTING MODELS, MEASURED AND OPTIMIZED MODEL OF BTS1

Distance (km)	SUI C Model (dB)	Okumura Hata Model (dB)	Egli Model (dB)	Cost 231 Model (dB)	Measured (dB)	Optimized Model (dB)
0.112	85.2949	147.2408	68.1309	93.9246	118	125.685
0.2	96.0598	156.2414	78.2033	102.9253	134	130.743
0.302	103.7111	162.6387	85.3624	109.3225	138	134.309
0.4	108.9288	167.0013	90.2445	113.6851	139	136.790
0.5	113.0718	170.4652	94.1209	117.1491	141	138.7372

TABLE 5: PATH LOSS VALUES FOR EXISTING MODELS, MEASURED AND OPTIMIZED MODEL OF BTS2

Distance (km)	SUI b Model (dB)	Okumura Hata Model (dB)	Egli Model (dB)	Cost 231 Model (dB)	Measured (dB)	Optimized Model (dB)
0.2	74.6843	86.4236	74.7434	101.1075	123.863	127.411
0.4	80.3382	92.8947	87.4848	112.1818	132.884	128.834
0.6	87.4768	98.7068	94.1680	118.0002	128.868	129.548
0.8	93.2477	103.4054	99.5708	122.6989	130.738	130.104
1	97.1927	106.6175	103.2643	125.9109	129.759	130.616
1.2	100.4787	109.2929	106.3406	128.5863	132.863	130.976
1.4	103.4559	111.7169	109.1280	131.0103	134.859	1.31.130
1.6	105.9006	113.7073	111.4168	133.0008	131.792	131.330
1.8	108.1426	115.5332	113.5163	134.8267	130.814	131.585
2	110.1668	117.1809	115.4109	136.4743	131.766	131.825
2.2	111.8013	118.5116	116.9411	137.8050	135.819	132.150

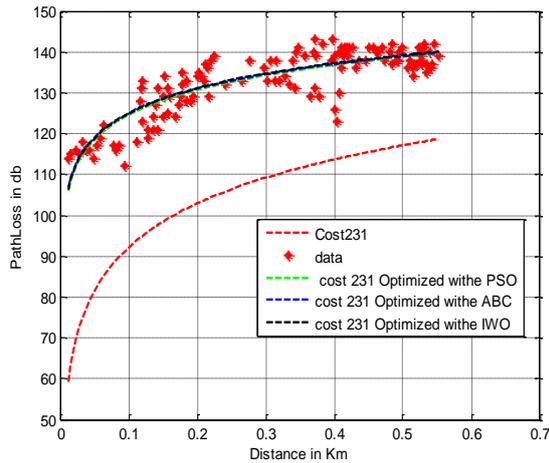


Fig 9. Comparison between COST-231 and optimized models (BTS1).

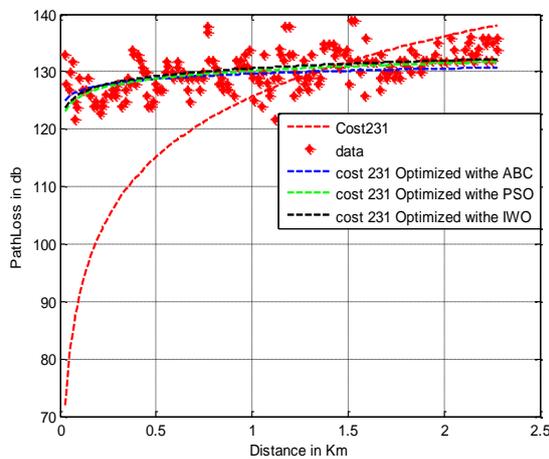


Fig. 10. Comparison between COST-231 and optimized models (BTS2).

TABLE 6. PERFORMANCE COMPARISON BETWEEN MEASURED AND TUNED MODELS ACCORDING TO THE TEST CRITERIA (RMSE).

Base station	Cost 213	Cost IWO	Cost ABC	Cost PSO	Cost GA (Test 03) [5]	Cost N-M [6]
BTS1	27.2553	4.142	4.1514	4.1427	5.4327	4.1614
BTS2	14.4196	3.038	3.0681	3.0493	3.0682	3.1681

From the optimization process of Cost 231 model, the developed models demonstrated better prediction compared to the existing models in terms of overall performance as shown in table 6. This remark is highlighted by the figures 9 and 10.

A closer look at table 6 turns out that the IWO method provides the lowest RMSE values in the two cases compared to the other proposed methods in one hand and to genetic algorithm and Nelder-Mead optimization proposed in [5] and [6] on the other hand.

The convergence speed of these methods during the optimization process is represented in figure (11), the IWO algorithm can converge rapidly compared to the other competitors.

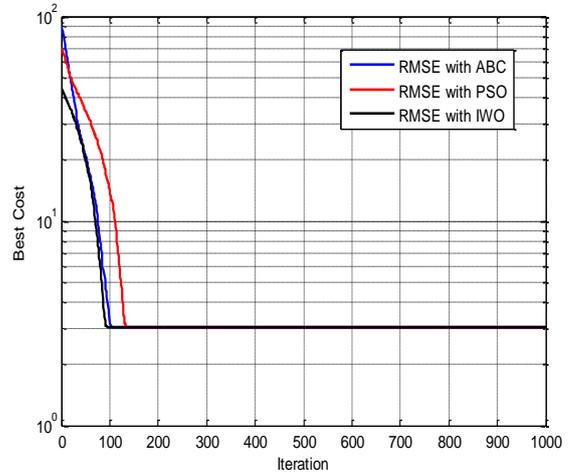


Fig 11. Fitness function evolution versus number of iterations

## V. CONCLUSION

Three optimization algorithms were proposed and tested in this paper to tune the parameters of Cost 231 Hata Model. Because, there is a need for considering the topology factor in propagation prediction models to achieve optimum design, the tuning models were verified by comparison with the measurements collected by the test driver technique in the rural and suburban environments in Batna city. The comparison results show a high degree of reduction in the path loss prediction. The slight superior performance of the IWO algorithm can be ascribed to two causes. First, The IWO can converge rapidly than the other proposed methods. Second, the IWO model can provide optimal parameters for radio-wave path-loss predicting with the smallest RMSE. Also a comparison with reference [5] and [6] confirms the same remarks obtained before. From the numerical results, 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 a good candidate for rural and suburban area of Batna.

For future work, forecasting other environments (Urban area) of path-loss data, taking in consideration the atmospheric factor, by using more powerful algorithm for propagation prediction models, to achieve optimum design of next

generation communication systems is a challenging issue for study.

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