# Propagation Model Optimization based on Particles Swarm Optimization and Genetic Algorithm Cross Implementation Application to Yaoundé Town

Deussom Djomadji Eric Michel
Department of Electrical and Telecommunications Engineering; College of Technology, University of Buea, Cameroon

Kabiena Ivan Basile
Department of Computer Engineering and telecommunications, National advanced school of Engineering, University of Douala, Cameroon

Tonye Emmanuel
Department of Electrical and Telecommunications Engineering; National Advanced School of Engineering of Yaoundé; University of Yaoundé I, Cameroon

## ABSTRACT
Propagation models are keys components of coverage planning. With the deployment of 4G and 5G network worldwide, operators need to plan the coverage of their network efficiently, in order to minimize deployment cost and improve the quality of service.

In this paper, the standard model K factors is used to develop a method for tuning propagation models based on cross implementation of both particle swarm optimization algorithm and genetic algorithm. The data were collected on an existing CDMA2000 1X-EVDO rev B network in the town of Yaoundé, capital of Cameroon. The root mean squared error (RMSE) between actual measurements and radio data obtained from the prediction model developed is used to test and validate the proposed method. The values of the RMSE obtained by the new model and those obtained by the standard model of OKUMURA HATA in urban area are also compared. Through the comparison of statistics from optimized model and OKUMURA HATA, we can show that the method is capable to optimized propagation model and the new model has a better precision and is more accurate than standard OKUMURA HATA model. The new model is also more representative of the local environment and the proposed method can be applied anywhere to optimize existing propagation models.

## General Terms

Propagation model optimization

## Keywords
Radio measurements, Radio propagation, model optimization, root mean square error.

## 1. INTRODUCTION
A propagation model suitable for a given environment is the key for the planning phase of the construction or the expansion of mobile networks, digital television broadcasting and newly develop network like LoRaWAN, Sigfox dedicated for internet of things. With the increasing demand in one hand of high speed data services for public commercial network, private network for ports, airports etc., governments private network for police, urban video surveillance and so one and in other hand of IoT solutions for smart cities initiative, smart agriculture, pollution control, smart fishing and so one, a particular emphasis must be made on the radio network dimensioning. For all these mentioned points, we need a proper propagation model which can be adapted to the local environment where we have to construct the new network (for example LoRaWAN, Sigfox, NB-IoT, LTE-M for IoT transport network) and possible and we can. To determine the characteristics of a radio propagation channel, tests of the real propagation models and calibration of the existing models are required to obtain a propagation model that accurately reflects the characteristics of radio propagation in the given environment.

The proposed propagation model optimization approach in this paper is based on a combination of genetic algorithm (GA) [1] [2] and particles swarm optimization (PSO) algorithm [3] [4] [5], by using k factors model with six coefficients proposed by authors in [6] and [7], up to 6 parameters of the proposed model can be optimized compared to linear regression mostly used by authors worldwide which is limited on the optimization of only 2 parameters. In addition GA and PSO combination algorithm can output not only one solution, but a set of possible solutions, among them the best one is selected as final one. Furthermore the solution has more diversity compare to that of linear regression method. This article will be articulated as follows: in section 2, the background of the work is presented, followed in section 3 by the experimental details. Next a description of the methodology adopted is presented in section 4. The results of the implementation of the algorithm, the validation of the results and comments will be provided in section 5 and finally we have a conclusion in section 6.

## 2. BACKGROUND
In population based optimization, many researchers have developed and proposed numerous algorithms with inspiration from nature for solving various optimization problems. Genetic Algorithm (GA) cited as an example and proposed by authors in [1] [2] [8] [9] are widely used, Particle Swarm Optimization (PSO) [3] [4] [8], and Artificial Bee Colony (ABC) [10] [11] [12] [13] [14] are also widely used and some variants of these algorithms are being developed and proposed by authors. A new physics-inspired metaheuristic optimization algorithm based on the motion of ions in nature called Ion Motion Optimization (IMO) was published in 2015 [15] and is gradually tested and used for many kind of optimization problems, author in [16] used this algorithm to optimize propagation model with very good results. These algorithms

have advantages and disadvantages compared to each other and may show different performances when solving discrete and continuous problems.

As PSO and GA have been rove to efficiently solve many kinds of optimization problem including the optimization of propagation model in [6] and [7], through this work we test and evaluate the combination of both PSO and GA capability to solve propagation model optimization problem which aims to build an appropriated propagation model related to a specific environment for network planning and deployment. Based on the hypothesis that the standard propagation models currently implemented in Cameroon have been developed in other countries and therefore do not accurately reflect the characteristics of the physical environment of Cameroonian cities; PSO and GA combined can be used to optimize Okumura Hata propagation model or any other propagation model for different types of deployment like mobile network, digital television, NB-IoT for smart metering solution like the one propose by authors in [17].

This work is not the first to focus on the optimization of propagation models. Indeed, several people from various backgrounds have already addressed the issue, each tackling a specific aspect of the problem or prove the capability of population based algorithm to optimize propagation model. For example, Deussom Eric et al in [18] worked on "Social Spider Algorithm-based Approach for Propagation Model Optimization"; Deussom Eric and Tonye Emmanuel [19] worked on "Propagation model optimization based on Artificial Bee Colony algorithm: Application to Yaoundé town, Cameroon; Deussom Eric and Tonye Emmanuel have also proposed other methods for propagation model optimization in [20] [21] [22] [23][24].

In this study, we will do a cross implementation of PSO and GA to optimize propagation model in 800MHZ spectrum, precisely between 870MHz- 880 MHz by using data collected in 04 parts of the town of Yaoundé which is the capital of the republic of Cameroon.

## 2.1 Propagation model

### *2.1.1 K factors propagation model [9]*

There are many propagation models presented in scientific literature, but this modeling is based on K factor propagation model.

The General form of the K factors model is given by the following equation:

$$L_p = K_1 + K_2\log(d) + K_3{*}h_m + K_4{*}\log(h_m) + K_5{*}\log(h_b) + K_6{*}\log(h_b)\log(d) + K_{7diffn} + K_{clutter} \quad \textbf{(1)}$$

$K_1$ constant related to the frequency, $K_2$ constant of attenuation of the distance or propagation exponent, $K_3$ and $K_4$ are correction factors of mobile station height; $K_5$ and $K_6$ are correction factors of BTS height, $K_7$ is the diffraction factor, and $K_{clutter}$ correction factor due to clutter type.

The K parameter values vary according to the type of the landscape and the characteristics of the propagation of the city environment; the following table gives values of K for a medium-sized town.

Eq. (1) could also be written in the following form:

$$\mathbf{L_p = (K_1 + K_{7diffn} + K_{clutter}) + K_2\log(d) + K_3 * h_m + K_4 * \log(h_m) + K_5 * \log(h_b) + K_6\log(h_b)\log(d)}$$

Assuming $K_1' = (K_1 + K_{7diffn} + K_{clutter})$ , Eq. (1) gets the form below:

$$\mathbf{L_p = K_1 + K_2\log(d) + K_3 * h_m + K_4 * \log(h_m) + K_5 * \log(h_b) + K_6\log(h_b)\log(d)} \quad \textbf{(2)}$$

Our main contribution on this paper is the proposal a new approach of optimizing propagation model by combining GA and PSO, then we test the proposed solution on drive tests data collected on an existing network for testing and implementation.

# 3. EXPERIMENT

## 3.1 Propagation environment

In this study, the data is collected from 4 BTS distributed throughout the city of Yaoundé on a CDMA1X EVDO RevB network. The BTS represent Yaoundé downtown and the transition from downtown to the suburb areas. For each category, similar environments are used, and results compared. The table below presents the categories according to the position of the BTS.

**Table 1: Types of environment**

| Categories | A | B |
|---|---|---|
| Urban characteristics | Dense urban | Urban |
| Concerned BTS | Ministere PTT (A1)<br>Bastos (A2) | Hotel du plateau (B1)<br>Biyem Assi (B2) |

## 3.2 Equipments description

### *3.2.1 Simplified description of BTS used.*

BTS involved in our data collection process are HUAWEI Technologies manufactured. The following table shows the specifications of the BTS

**Table 2: BTS characteristics**

| | BTS3606 | DBS3900 |
|---|---|---|
| BTS types | Indoor BTS | Distributed BTS (Outdoor) |
| Number of sectors | 3 | 3 |
| Frequency Band | Band Class 0 (800 MHz) | Band Class 0 (800 MHz) |
| Downlink frequency | 869 MHz - 894 MHz | 869 MHz - 894 MHz |
| Uplink frequency | 824 MHz - 849 MHz | 824 MHz - 849 MHz |
| Max power (mono carrier) | 20 W | 20 W |
| BTS Total power (dBm) | 43 dBm | 43 dBm |

The BTS engineering parameters are presented in the tables below.

**Table 3: BTS engineering parameters (1)**

| BTS Type | BTS name | Latitude (degree) | Longitude (degree) | BTS Altitude (m) |
|---|---|---|---|---|
| 3606 | MinistryPTT | 3.86587 | 11.5125 | 749 |
| 3900 | Hotel du plateau | 3.87946 | 11.5503 | 773 |
| 3606 | Biyem-Assi | 3.83441 | 11.4854 | 721 |
| 3900 | Camtel Bastos | 3.89719 | 11.50854 | 770 |

**Table 4: BTS engineering parameters (2)**

| BTS name | Antenn a height | Mean elevation | Antenna effective height | Antenn a's Gain （ dBi) | 7/8 Feeder Cable( m) |
|---|---|---|---|---|---|
| MinistryPT T | 40 | 741.82 | 47.18 | 15.5 | 45 |
| Hotel du plateau | 27 | 753.96 | 46.04 | 17 | 0 |
| Biyem-Assi | 40 | 709.54 | 51.46 | 15.5 | 45 |
| Camtel Bastos | 28 | 754.86 | 43.14 | 17 | 0 |

Fig. 1 and Fig. 2 are samples of drive test done in the area A1 and A2

The drive test tools used for data collection are: pilot pionner software from Dinglicom, a laptop, a DC/AC converter to supply power to the laptop, a LG CDMA terminal, a dongle and a GPS receiver all install inside a Car. Fig. 3 is the collection tool install in a car.

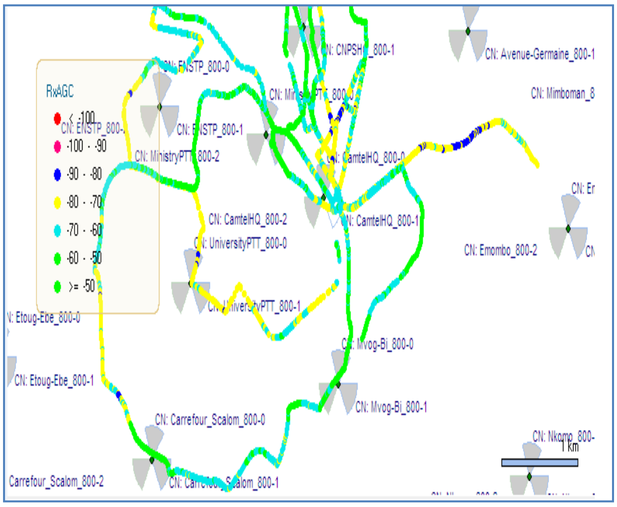


**Fig. 1: Drive test in centre town (A1)**

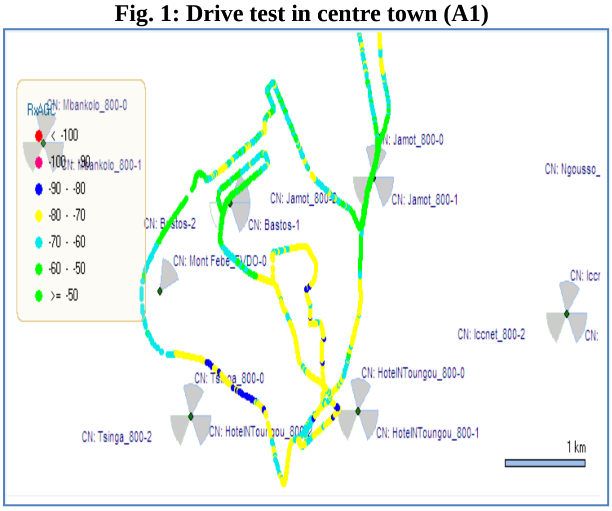


**Fig. 2: Drive test in Bastos area (A2)**

# 4. METHODS

There are many propagation models presented in scientific literature, but our modeling is based on the K factor propagation model, in fact almost every propagation model can be written in the form of K factors propagation model in a specific frequency. First let remind Okumura Hata model.

Okumura Hata model for urban area and frequency greater than 300MHz is given by the following formula:

$$\boldsymbol{L_{dB} = A + B\log(d) - E,} \tag{3}$$

With $A = 69.55 + 26.16\log(f_c) - 13.82\log(h_b)$
$B = 44.9 - 13.82\log(h_b)$ , $E = 3.2(\log(11.75h_m))^2 - 4.97$, in fact for $h_m = 1.5m$ , $E = 9.19 * 10^{-4} \approx 0$

Then Eq. (3) can be simplified as

$$\boldsymbol{L_{dB} = 69.55 + 26.16\log(f_c) - 13.82\log(h_b) + (44.9 - 13.82\log(h_b))\log(d)} \tag{4}$$

## 4.1 Flowchart

Figure 3 is the flowchart that represents the determination of the propagation model using PSO and GA cross implementation. Data filtering is made according to the criteria for distance and signal strength received (see table 5)

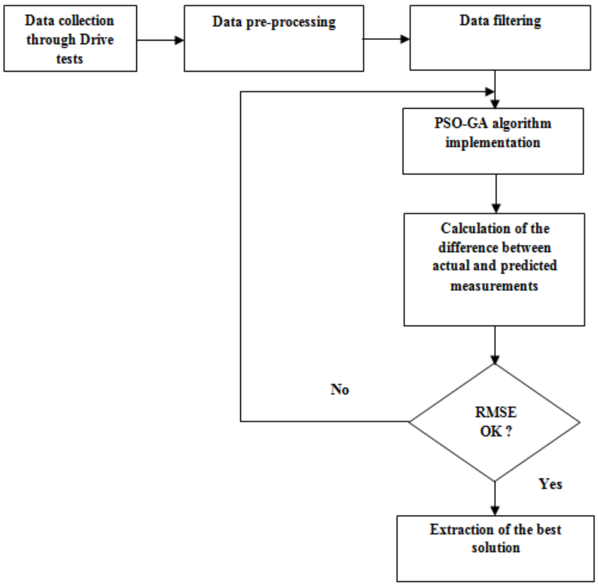


**Fig. 3: PSO-GA cross implementation flowchart**

| | |
|---|---|
| Minimum distance (m) | 100 |
| Maximum distance (m) | 10 000 |
| Minimum received power (dBm) | -110 |
| Maximum received power (dBm) | -40 |

**Table 5. Filtering criteria for distance and received power**

## 4.2 GA and PSO optimization algorithm.

PSO like GA algorithms find a solution by searching an extremum (maximum or minimum) on a set of possible solutions, the solution set is called a search space. PSO-GA algorithm is built using the procedure described by figure 3.

*4.2.1 Modeling of the problem by PSO-GA algorithm.*

We are trying to find a propagation model to suit any environment. Based on K factors model, Eq. (2) above can be written in matrix form as follows:

$$\boldsymbol{L = [K_1\ K_2\ \ K_3 K_4\ K_5\ K_6\,] * \begin{bmatrix} 1 \\ log(d) \\ H_m \\ log(H_m) \\ log(H_{eff}) \\ log(H_{eff}) * log(d) \end{bmatrix}} \quad \textbf{(5)}$$

In Eq. (5) only the vector K=$[K_1\ K_2\ \ K_3 K_4\ K_5\ K_6\,]$ **(6)** is variable depending on the values of, i $\boldsymbol{\epsilon\{1,2,3,4,5,6\}}$ and j an integer. Let:

$$\boldsymbol{M = \begin{bmatrix} 1 \\ log(d) \\ H_m \\ log(H_m) \\ log(H_{eff}) \\ log(H_{eff}) * log(d) \end{bmatrix},} \quad \textbf{(7)}$$

Therefore L can be written in the form

$$\boldsymbol{L = K * M} \quad \textbf{(8)}$$

With M a constant vector for a given distance d and depending on whether we were under a base station of effective height $H_{eff}$.

If in the contrary the distance d varies for different measurement points, vector M becomes a $M_i$vector for various measures at different distances points $d_i$ .

The determination of the vector K leads to the knowledge of our propagation model L. Our searching area is therefore the one that containing all the possible values of the vectors of the form presented as K above in Eq. (14). So K vectors are suitable for modeling either a chromosome for GA or a particle for PSO, then it can also be used for combination of the two algorithms.

**Table 6. Existing Propagation models on the form of K vector.**

| Propagation model | K1 | K2 | K3 | K4 | K5 | K6 |
|---|---|---|---|---|---|---|
| Okumura Hata | 146.56 | 44.9 | 0 | 0 | -13.82 | -6.55 |
| Free space | 91.28 | 20 | 0 | 0 | 0 | 0 |
| K factors | 149 | 44.9 | -2.49 | 0 | -13.82 | -655 |

The first 3 particles or chromosomes of the initial swarm will be the particles corresponding to Okumura Hata model, standard K factors and free space propagation models above. The other particles need to be generated in order to complete the size of the swarm to Nc individuals.

### *4.2.2 Comparison between GA and PSO for this special case of propagation model optimization.*

The GA and PSO algorithms as defined start from a randomly generated starting family, both use the evaluation of individuals, operations on individuals, an update of these and a search for the optimum, if the stopping criterion is reached, the algorithm is stopped, otherwise the evaluation is restarted and so on. The 2 algorithms do not always guarantee obtaining the desired optimum, but a good approximation of that optimum. Before the implementation of those 02 algorithms to optimize a propagation model, let presents a comparison between them to show that the variable, the evaluation functions that we can use for GA can be the same for PSO, through this we can use both of them sequentially to solve the optimization problem presents in this paper.

We have the summary tables below which give us a comparison between GA and PSO algorithms. Table 7 presents the similarity between GA and PSO while table 8 and table 9 present a comparison between the two algorithms.

**Table 7: Similarity between GA and OEP**

| | AG | OEP |
|---|---|---|
| Family size | **Nc** chromosomes | **Nc** particles |
| Type of coding of individuals | Real coding | Real coding |
| Number of iterations | **Ng** generations | **Nd** displacements |
| Evaluation function | RMSE | RMSE |

**Table 8: Comparison between GA and PSO**

| N° | Algorithms | Variable name | Set of variables | Fixed set size | Evaluation type |
|---|---|---|---|---|---|
| 1 | GA | Chromosome or individual | Family | Yes | Fitness |
| 2 | PSO | Particle | Swarm | Yes | Fitness |

**Table 9: Similarities between GA and OEP parameters**

| N° | Algorithms | Number of iterations | Operation on the set | Information Sharing Mode | Type of information sharing |
|---|---|---|---|---|---|
| 1 | GA | Number of generations | Selection, crossing and mutation | crossing | From Tc*Nc to Tc*Nc |
| 2 | PSO | Number of displacements | Speed update and displacement | Remembering Xpbesti and Xvbesti | 1 to N (Xvbest to entire swarm) |

In the table above Tc is the crossover rate and Nc the number chromosomes of the family for the GA.

We will then introduce the cross implementation of PSO and GA also called PSO-GA in this paper.

- **Modeling by cross-implementation of PSO and GA.**

For both GA and PSO, the evaluation functions in the 2 cases can be similar or even identical, the number of displacements can also be assimilated to the number of generations, and the size of the swarm is also similar to the size of the family. We therefore see that it is possible to implement for a given problem both PSO and GA simultaneously.

Ming Li and al in “Particle Filter Improved by Genetic Algorithm and Particle Swarm Optimization Algorithm” [15] implemented this cross algorithm for solving some complex optimization problems. In this case, we will first present some implementation conditions.
The implementation will be conditioned by the constraints below presented in table 9.
The cross implementation of PSO and GA can be seen as a swarm in displacements which also do reproductions.

# 5. RESULT AND COMMENTS

The implementation of PSO-GA as described above on the radio measurement data obtained in Yaoundé was done by setting the parameters as follows:
Nc = 60; Nit=Ng=20; c1=2; c2=2, Tc=0.6; Tm=0.01; alpha=0.6. Remember, however, that Nc is the number of particles in the swarm, which also corresponds to the number of chromosomes for GA, Nit the number of displacements of the swarm, which again corresponds to the number of iterations of the algorithm and also to the number of generations for GA. c1 and c2 are PSO parameters, Tc and Tm are respectively the crossing and mutation rate for GA. We obtained the results by zone presented in the following paragraphs. The model will be seen as accurate if the RMSE between the values of prediction and measured is less than 8 dB; (RMSE < 8dB). [20]

## 5.1 Results by area

After the implementation of the both PSO and GA combined as described above, we obtain the representatives curves below, the actual measurements are in blue, Okumura Hata model in green, and the free space propagation model in yellow and the new model obtained via PSO-GA in red.

### *5.1.1 Case of centre town*

At the end of the implementation of the algorithm crossed on the data of radio measurements of the city center of Yaoundé, we obtained the vector solution contained in the table 10 while table 11 presents the statistical parameters obtained after the implementation of the algorithm.

**Table 10: Results of the optimization by the cross algorithm in the centre town.**

| Zone | K1 | K2 | K3 | K4 | K5 | K6 | RMSE |
|---|---|---|---|---|---|---|---|
| A1 | **124.17** | **37.62** | **-2.49** | **0** | **-8.20** | **-6.55** | **6.71** |

**Table 11: Statistical parameters of the cross algorithm for the city center**

| Zone | RMSE | Standard deviation (σ) | Mean error |
|---|---|---|---|
| A1 | **6.7159** | **6.7148** | **1.4184** |

From the table above, we see that the new model optimized by the implementation of PSO and GA combined gives us a better result than the standard models of OKUMURA HATA and K factors, the RMSE obtained is equal to 6.71dB which is less than 8dB (consider as the upper threshold). The representative curve given by figure 4 is in conformity with the cloud of points representing the actual measurements, where in red we have the curve obtained by the optimized model, in bleu we have the real data, in black the curve obtained by plotting Okumura Hata model and in yellow the plot of free space propagation model. The x-axis represents the distance

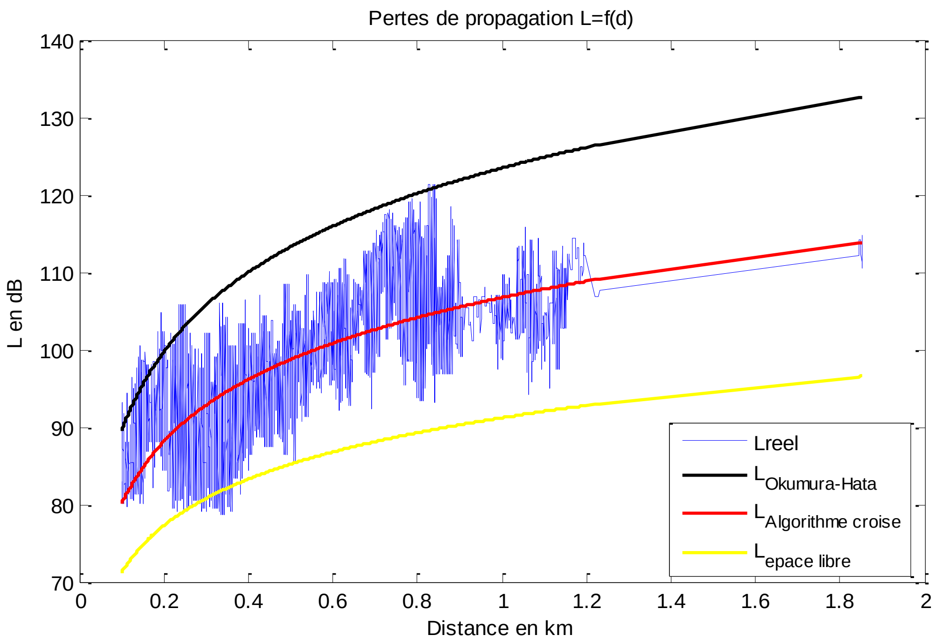


**Fig. 4: Results of the optimization in the city center**

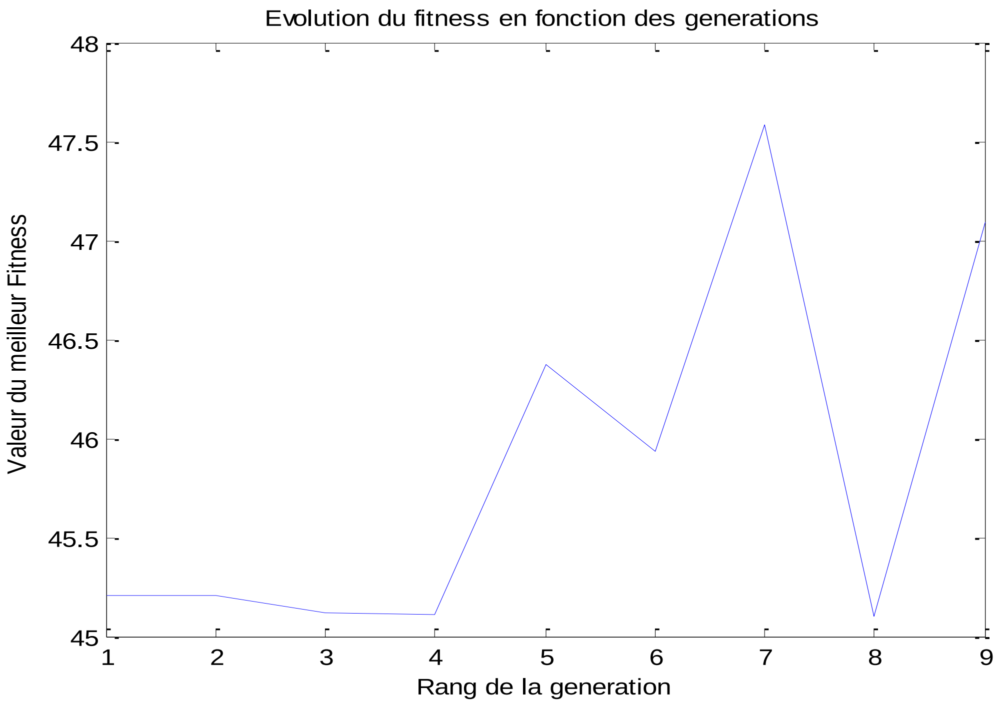


**Fig.5: Fitness evolution after implementation of the algorithm.**

The combined implementation of PSO and GA algorithm makes it possible to obtain an optimized model that is precise and representative of the data collection environment, however with regard to the fitness curve, the fitness suffers from instability in terms of monotony, it is not strictly decreasing like those of the AG or the OEP, therefore, the result obtained at the end of the algorithm is not the best solution obtained by all the variables constituting the space of solutions during the displacements/reproduction of the swarm. Nevertheless, we have good results. By comparing, for example, the RMSE obtained for the city center data between the cross algorithm (RMSE=6.7159), the GAs (RMSE=6.7164) and the OEP (RMSE=6.7224), we are surprised to see that the PSO-GA cross implementation gives the best RMSE, and therefore is more accurate than the others.

*5.1.2 Case of others 3 parts of the town.*

The tables 12 and 13 below give us the results obtained for zones A2, B1, B2 corresponding respectively to the Bastos, Biyem Assi and Essos Camp Sonel districts at the end of the implementation of the combined PSO-GA algorithm.

From those tables, it appears clearly that the optimization by the cross implementation PSO-GA algorithm makes it possible to have for all the zones good results satisfying the criteria of a RMSE less than 8dB. For the 3 areas considered the RMSE are good.

It should also be noted that genetic algorithms allow, at the end of a certain number of reproductions, to have "similar" individuals because of the processes of selection, crossing and mutation applied, if moreover the crossing scheme is elitism, we can at least guarantee that after a number of iterations, we could have good solutions, this also the case for PSO and by combining PSO and GA we can inherit the advantages of both and obtained a good solution after the implementation of the algorithm. PSO-GA is a good option to solve optimization problem as it is the case for the specific problem of propagation model optimization.

**Table 12: Results of the PSO-GA implementation for areas A2, B1, B2**

| Results | Zones | K1 | K2 | K3 | K4 | K5 | K6 | RMSE |
|---|---|---|---|---|---|---|---|---|
| **PSO -GA implementation** | A2 | 111.80 | 28.36 | -2.49 | 0 | 2.65 | -6.55 | 6.1140 |
| | B1 | 130.31 | 18.48 | -3.41 | 0 | -13.82 | -6.55 | 5.3920 |
| | B2 | 124.12 | 33.81 | -2.49 | 0 | -3.5948 | -6.55 | 7.3949 |

**Table 13: PSO-GA statistical parameters for areas A2, B1, B2**

| Results | Zones | RMSE | Standard deviation (σ) | Mean error |
|---|---|---|---|---|
| **PSO -GA implementation** | A2 | 6.1140 | 6.1108 | 0.3655 |
| | B1 | 5.3920 | 5.5183 | -0.2956 |
| | B2 | 7.3949 | 7.4265 | 0.6601 |

Finally, the average K vector is **K= [122.6; 29.57; -2.72; 0 ; -5.74; -6.55]** can be used as final propagation model.

# 6 CONCLUSION

This paper presents a new method for the optimization of propagation model relatively to a given environment based a combination of PSO and GA algorithms. This research is focused not in a specific propagation model like Okumura Hata or Walfisch-Ikegami, but in the general form that a propagation model could have in a specific frequency: the K factor model. The advantage of doing this is that almost all existing statistical propagation models on a specific frequency could be written in the form of Eq.(2) with 6 coefficients or Eq.(5) which is a factorized form of Eq.(2). Then we can model the family of individuals as a set of particles or chromosomes in the form of Eq.(5) and fully design the algorithm. It has also been proposed a complete implementation algorithm and comparative tables between PSO and GA in other to justify how they can be combined in the same implementation using the same mathematical model. After this, by using drive tests data collect from field measurements, code have been developed and run by using Matlab to test the proposed algorithms, then results have been output and their analysis shows that the proposed method and algorithm can well optimized propagation models.

The method like linear regression when used can only optimize 2 parameters amongst the 6 of the K factors model with 6 coefficients, while PSO-GA implemented in this paper can optimized all the 6 coefficients of K factors model.

At the end, we can conclude that PSO-GA implementation on measurements done in the city of Yaoundé as application case gave us very good results with a RMSE less than 8dB in all the selected areas in the city. Compared to Okumura Hata's RMSE obtained, the new model gives a better and accurate result which can be used for network planning.

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