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Okumura Hata Propagation Model Optimization in 400 MHz Band Based on Differential Evolution Algorithm: Application to the City of Bertoua

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Abstract

Propagation models are the foundation for radio planning in mobile networks. They are widely used during feasibility studies and initial network deployment, or during network extensions, particularly in new cities. They can be used to calculate the power of the signal received by a mobile terminal, evaluate the coverage radius, and calculate the number of cells required to cover a given area. This paper takes into account the standard k factors model and then uses the differential evolution algorithm to set up a propagation model adapted to the physical environment of the Cameroonian cities of Bertoua. Drive tests were made on the LTE TDD network in the city of Bertoua. Differential evolution algorithm is used as the optimization algorithm to deduct a propagation model which fits the environment of the considered town. The calculation of the root mean square error between the actual data from the drive tests and the prediction data from the implemented model allows the validation of the obtained results. A comparative study made between the RMSE value obtained by the new model and those obtained by the Okumura Hata and free space models, allowed us to conclude that the new model obtained is better and more representative of our local environment than the Okumura Hata currently used. The implementation shows that Differential evolution can perform well and solve this kind of optimization problem; the newly obtained models can be used for radio planning in the city of Bertoua in Cameroon.

Keywords

Radio Measurements, Root Mean Square Error, Differential Evolution Algorithm

1. Introduction

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] and [2] are widely used, Fogel in [3] has presented more details about evolutionary computation, Goldberg in [4] has proposed and developed in 1989 the usage of GA for optimization and machine learning, while author Mitchell in [5] has presented and introduction with more details on genetic algorithm. In the same way like GA, Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart in [6] and [7], in [8], the same authors have presented the point related to the explosion, stability and convergence in multi-dimensional complex space of PSO. Authors in [9] have presented a proposal for "Dynamic Diversity Enhancement in Particle Swarm Optimization algorithm for preventing from premature convergence", with the objective of improving PSO initial implementation parameters. Same as PSO and GA, Artificial Bee Colony (ABC) was proposed by authors in [10] and [11], and in [12] the same authors have presented the On the performance of artificial bee colony, while authors in [13] proposed "a comparative study of artificial bee colony algorithm", W. Gu, M. Yin and C. Wang in [14] proposed a Self adaptive artificial bee colony for global numerical optimization with the aim of improving the application field of ABC. All these algorithms are 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 kinds of optimization problems. These algorithms have advantages and disadvantages compared to each other and may show different performances when solving discrete and continuous problems.

As DE is a newly developed algorithm proposed by Storn and Price in [16] and [17], through this work we test and evaluate its capability to solve propagation model optimization problem which aims to build an appropriated propagation model related to a specific of environment for network planning and deployment. The objective of this study is to integrate the use of the DE algorithm in the resolution of a real problem in the field of telecommunications, which is optimizing propagation models. 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; DE, a new population-based algorithm would be appropriated to optimize the Okumura Hata 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 [18].

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 part of the network. For example, Deussom Eric and Tonye Emmanuel [19] worked on "New Propagation Model Optimization Approach based on Particles Swarm Optimization Algorithm"; Deussom Eric and Tonye Emmanuel [20] worked on "Propagation model optimization based on Artificial Bee Colony algorithm: Application to Yaoundé town, Cameroon; Deussom eric *et al.* has used Social Spider Algorithm in [21] for Propagation Model Optimization. Deussom Eric and Tonye Emmanuel have also proposed other methods for propagation model optimization in [22], in [23] the same authors proposed a solution for propagation model optimization based on GA; in [24] the same authors used Newton second order algorithm to optimize propagation model and linear regression in [25].

In this study, we will in the first part evaluate and validate the performance of the DE algorithm in solving complex problems through drive test data collected in the LTE TDD network in 380 - 400 MHZ band of the city of Bertoua and we will apply it in the optimization of the Okumura Hata propagation model. Through this research work we expand the usage field of DE algorithm by proving that same as other algorithm, it can optimize propagation model. This article will be articulated as follow: in Section 2, the experimental details will be presented, followed by a description of the methodology adopted in Section 3. The results of the implementation of the algorithm, the validation of the results and comments will be provided in Section 4 and finally a conclusion will be presented.

2. Experimental Details

2.1. Propagation Environment

The city of Bertoua (regional capital of east region with a different type of urbanization compare to Yaoundé town), is located at a latitude of 4˚34'30" north, longitude of 13˚41'04" east, the altitude is 717 m and is the town on which the present study is based. We relied on the existing LTE TDD network to make radio measurements. We selected 3 areas where we consider 03 BTS namely Bertoua Lycee, Bertoua central and Bertoua CRTV (**Figure 1**).

2.2. Equipment Description

2.2.1. Simplified Description of eNodeB Used

In Bertoua town for the considered network, the enodeB used for drive tests is provided by Huawei, DBS3900 LTE TDD working in the frequency band of 380 - 400 MHz. **Table 1** presents the radio parameters used on this eLTE network.

Figure 1. Position of the 3 BTS in the town of Bertoua in Cameroon, East region.

Table 1. eNodeB Radio parameters.

BTS name	Sector ID	PCI	Antennas height	Azimuth	Tilt
Bertoua CRTV	0	189	30	25	3
Bertoua CRTV	1	191	30	143	6
Bertoua CRTV	2	190	30	240	0
Bertoua Central	0	184	25	344	6
Bertoua Central	1	183	25	120	3
Bertoua Central	2	182	25	240	3
Bertoua Lycée	0	188	20	300	6
Bertoua Lycée	1	186	20	80	2
Bertoua Lycée	2	187	20	195	6

2.2.2. Other Equipment Parameters

To perform the drive tests. We used a Toyota pickup vehicle, an HP laptop, drive test software namely HUGELAND from the Chinese company Beijing Hugeland Technologies Co, a Huawei LTE TDD mobile terminal, a GPS terminal, a DC/AC converter to power the PC during the measurement. For the Bertoua town, which is a regional capital for east region in Cameroon, we have the drive tests done in 3 areas presented in Figures 2-4. Table 2 presents the statistics of RSRP after the drive tests carried in Bertoua.

3. Methodology

3.1. Propagation Model

Many propagation models exist in scientific literature, we present only the Okumura-Hata, free space and K factors models on which we relied for this work. The distance d is expressed in km and the frequency f in MHz.

3.1.1. Propagation Model K Factors

1) Description

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.

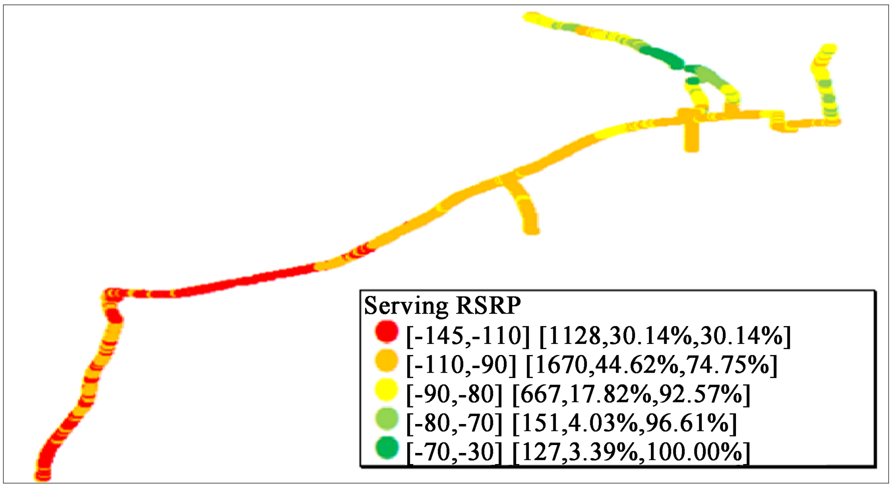

Figure 2. Drive test result of Bertoua CRTV.

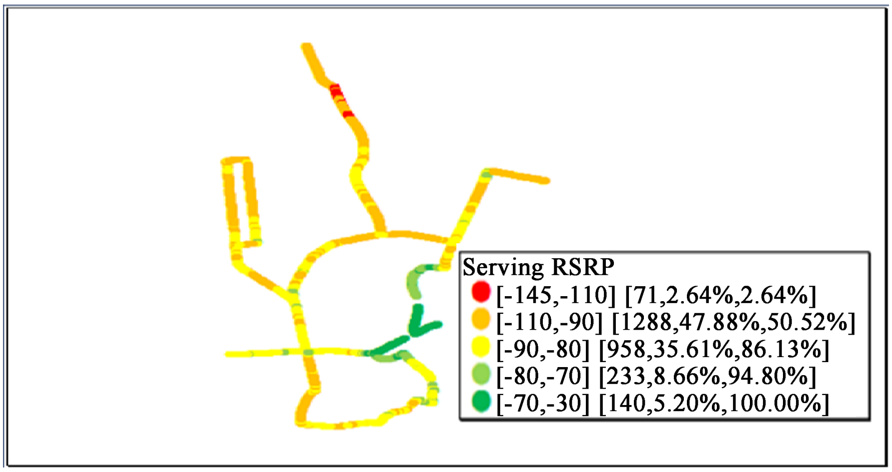

Figure 3. Drive test result of Bertoua Central.

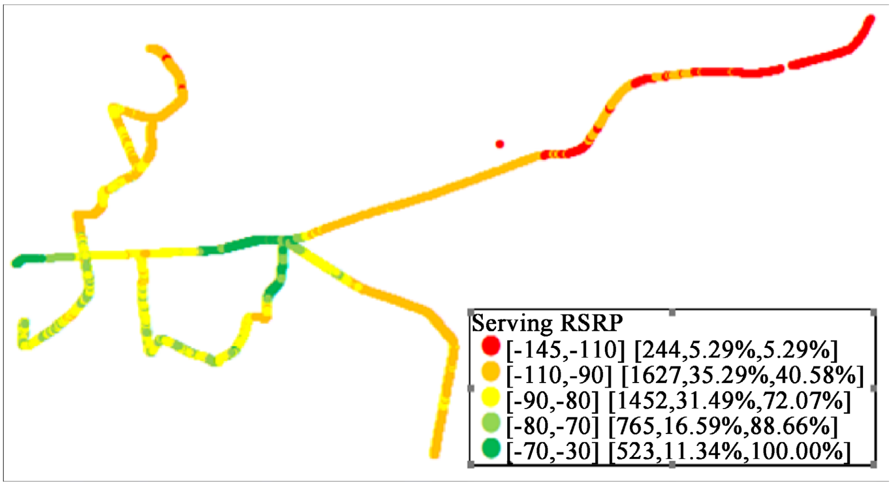

Figure 4. Drive test result of Bertoua Lycée.

Table 2. RSRP statistics from drive tests results per BTS site.

BTS	Average	Maximum	Minimum	Standard Deviation
Bertoua Central	−98.96	−45.95	−126.00	14.65
Bertoua CRTV	−98.96	−45.95	−126.00	14.65
Bertoua Lycée	−86.88	−44.38	−129.00	14.83

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

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 phone height; K_5 and K_6 are correction factors of BTS height, K_7 is the diffraction factor, and $K_{clutter}$ the 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;

Equation (1) could also be written in the factorized form (Equation (2)) as proposed by authors in [26] and [27].

$$L = [K_1\ K_2\ K_3\ K_4\ K_5\ K_6] \times \begin{bmatrix} 1 \\ \log(d) \\ H_m \\ \log(H_m) \\ \log(H_{eff}) \\ \log(H_{eff}) * \log(d) \end{bmatrix} \quad (2)$$

In Equation (2) the vector $K = [K_1\ K_2\ K_3\ K_4\ K_5\ K_6]$ (3)

$$\text{Let}\quad M = \begin{bmatrix} 1 \\ \log(d) \\ H_m \\ \log(H_m) \\ \log(H_{eff}) \\ \log(H_{eff}) * \log(d) \end{bmatrix} \quad (4)$$

Then propagation model in the form of K factors can be written as

$$L = K \times M \quad (5)$$

This expression will be considered as the factorized form of the propagation model.

3.1.2. Okumura Hata and Free Space Models

The Okumura-Hata and free space models are special cases of the K factors model. The Okumura-Hata propagation model [28] [29] is written by:

$$L_{dB} = 69.55 + 26.16\log(f_c) - 13.82\log(h_b) + [44.9 - 6.55\log(h_b)]\log(d) - E \quad (6)$$

With $E = 3.2(\log(11.75h_m))^2 - 4.97$ in fact for $h_m = 1.5\ \text{m}$,

$E = 9.19 \times 10^{-4} \approx 0$

The free space model on its own is given by the following expression:

$$L = 32.45 + 20\log(f_c) + 20\log(r) \quad (7)$$

The K values for these two models are as follows in **Table 3**.

3.2. Propagation Model Optimization Using DE

DE was proposed almost in the same time as PSO by Storn and Price (1995) for global optimization over continuous search space. Its theoretical framework is simple and requires a relatively few control variables but performs well in convergence. In DE algorithm, a solution is represented by a D-dimensional vector. DE starts with a randomly generated initial population of size N of D-dimensional vectors. In DE, the values in the D-dimensional space are commonly represented as real numbers. Again, the concept of solution representation is applied in DE in the same way as it is applied in GA and PSO. The key difference of DE from GA or PSO is in a new mechanism for generating new solutions. DE generates a new solution by combining several solutions with the candidate solution. The population of solutions in DE evolves through repeated cycles of three main DE operators: mutation, crossover, and selection. However, the operators are not all exactly the same as those with the same names in GA.

3.2.1. The Phases of the Differential Evolution Algorithm

1) *Initialization of the population*

The first phase of DE is the initialization of the population. We can see this phase as the beginning of the universe (of the algorithm) with the appearance of the first species. Here, our species are the set of potential solutions to the problem we are trying to solve. The idea is to find the best one. With the DE algorithm, any group of solutions of the same generation is called population. And the population generated during the initialization phase is called initial population. It is generated randomly. A generation is nothing but an iteration of the algorithm. It is important to define the data structure used with the DE algorithm. This data structure is called Chromosome. A chromosome is nothing more than a collection of genes. The genes are descriptive elements of each solution in the population.

2) *Evaluation*

Once our initial population is generated, the second phase of the algorithm is evaluation. It is in this phase that we will determine the quality of each solution (chromosome). To do so, we will have to define a function to estimate this quality called "fitness function". This function must take a solution (chromosome) as

Table 3. K values for the Okumura-Hata model and free space.

Model	K_1	K_2	K_3	K_4	K_5	K_6
Okumura Hata	$69.55 + 26.16\log(f) - E$	44.9	0	0	13.82	−6.55
Free space	$32.45 + 20\log(f)$	20	0	0	0	0

input and determine at which point it is optimal. This function is always defined by the creator of the algorithm and depends strongly on the problem studied. Then, this fitness/aptitude function is applied on all the chromosomes of the population and for each chromosome we record the value returned. This value is called score. The evaluation phase actually consists in comparing each chromosome score with the threshold convergence value defined beforehand.

3) *Mutation*

In the mutation stage, in order to create new individuals, individuals are modified by introducing more genetic material into the population. The role of mutation is to add diversity and avoid being trapped in local optima. In the case of DE, a new individual is created by adding a scaled differential term to a base vector (individual). This mechanism, also called "differentiation", is the main feature separating DE from other evolutionary algorithms:

$$W_i = \alpha + F \times \beta \quad \text{with:} \tag{8}$$

- W_i; *i*-th element of the mutated population;
- α; the base vector;
- $\beta = X_k - X_p$; the differential term
- F is the scaling factor.

The differential term is defined as the difference of two distinct vectors, chosen randomly, the base vector is also chosen randomly, and in order to achieve good convergence speed and probability, Price and Storn in [17] published (2005) state that all vectors used in the mutation step must be distinct.

4) *Crossover*

In this step, a population diversity improvement operation is applied. Using two populations (current and mutated), a new test population is created. Generally, two crossover variants are used in the DE algorithm: binomial [Equation (9)] and exponential.

$$U_{i,j} = \begin{cases} W_{i,j}; & \text{if } rand(0,1) < C_r \\ X_{i,j} & \text{otherwise} \end{cases}$$

- $U_{i,j}$; trial vector;
- $W_{i,j}$; mutant vector;
- $X_{i,j}$; *i*-th element of the actual population.

A control parameter (Cr) is used to control which components of each individual are copied and how many components of each individual are copied. It can take values in the range [0, 1], its optimal value being influenced by the type of problem and the type of crossover [30].

5) *Selection and stopping criteria*

In the final step of the algorithm, a mechanism for selecting the individuals forming the next generation is used. The classical version of DE uses a one-to-one competition, with the trial and the current individuals being compared according to their objective values. Those with the lowest value (when considering a minimization problem) are selected to form the next generation.

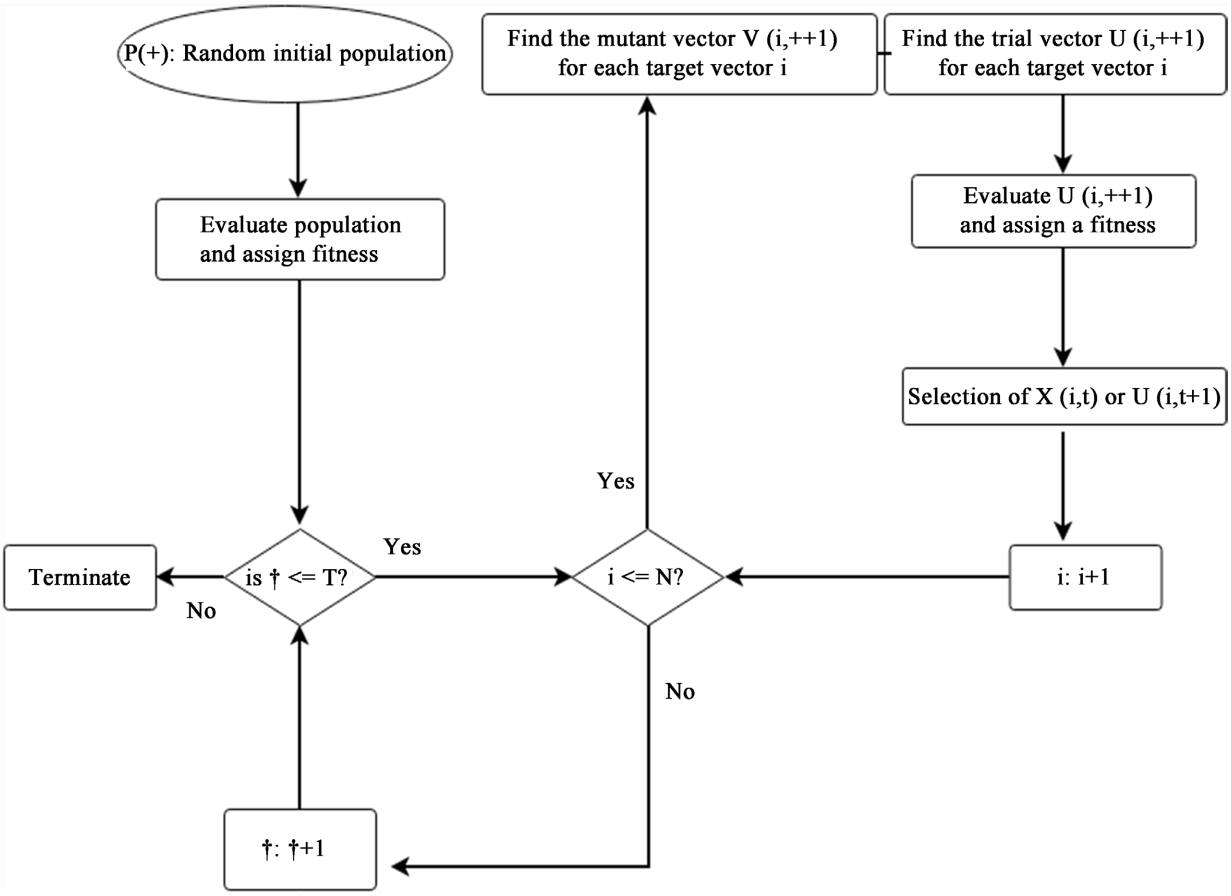

Figure 5. Flowchart of DE implementation.

3.2.2. Using of DE for Okumura-Hata Model Optimization

Figure 5 presents the flowchart of DE implementation.

1) *Generation of the initial population*

The search space is between the standard Okumura-Hata model and the free space propagation model which characterizes a propagation without obstacle. Now let us see how to generate the initial population.

The starting population that is generated is made up of different spiders K^j randomly generated, meeting certain criteria of integrity on the values of the different K_i^j for $i = 1{:}6$. Let F be the population. Then $F = \left[K_1^j\ K_2^j\ K_3^j\ K_4^j\ K_5^j\ K_6^j\right]_{j=1:N}$; Where N is the population size. The population is generated as follows:

Begin

$K1el = 32.4 + 20 \times \log10(Fc);$

$K1ok = 69.55 + 26.16 \times \log10(Fc);$

for $i = 1: N$

$K1 = K1el + (K1ok - K1el) \times rand(1);$

$K3 = -2.49 + 2.49 \times rand(1);$

$K4 = rand(1);$

$K5 = -13.82 + 13.82 \times rand(1);$

$K6 = -6.55 \times rand(1);$

$K2 = 20 - (K6 \times \log10(Hb)) + ((36.8 - 20) \times rand(1));$

$P(i,:) = [K1\ K2\ K3\ K4\ K5\ K6];$

End for

End;

This pseudo code is very important because it defines integrity constraints for each of the parameters K1, K2, K3, K4, K5 and K6. In this code, K1ok represents the parameter K1 in the Okumura-Hata model; K1el represents the parameter K1 in the free space model. P is the matrix representing the population generated and the size of the population corresponds to the number of distances measured. The initial population generated is an N × 6 matrix that is N rows and 6 columns. Then value of N corresponds to the number of distances measured and the value 6 represents the 6 parameters of the vector K = [K1 K2 K3 K4 K5 K6].

2) *Distances and pathloss calculation*

Table 4 presents the filtering criteria apply to driv tests data before running the proposed algorithm.

However, it is important to remember that the value of the measured losses (L_M) is not obtained explicitly from the radio measurements. It is obtained through the calculation of the link budget. The total power of an eNodeB is equally distributed over all available block resources, NRB = 5 × B, with B the available spectrum width in MHz. If the total power of eNodeB is P_{eNodeB} in W, the power per subcarrier will be:

$$P_{\text{sub-carrier(w)}} = \frac{P_{\text{eNodeB}}}{N_{\text{sub-carrier}}} \tag{9}$$

With $N_{\text{sub-carrier(w)}} = N_{RB} * 12$.

Each RB consists of 12 LTE sub-carriers. It is the power per subcarrier that is used in the link budget calculation.

$$\begin{aligned} L_M &= P_{\text{sub-carrier}} + \left(G_{\text{eNodeB}} + G_{\text{MS}}\right) \\ &\quad - \left(\sum Lf + \text{Penetration Loss} + M_I + M_{\text{Fading}}\right) - P_r \end{aligned} \tag{10}$$

With: penetration,

$P_{\text{sub-carrier}}$ is the sub-carrier power in dBm;

G_{eNodeB}, G_{MS}—the gains of the base station and mobile station in dBi;

$\sum Lf$ —the sum of other losses; M_i is the interference margin.

3.2.3. Evaluation of the Model

1) *Evaluation function*

Here, we have to minimize the Euclidean distance between the measured

Table 4. Filtering criteria [2].

Criterion	Distance (m)	Power (dBm)
Minimum	100	−110
Maximum	10,000	−40

values of the propagation loss and those predicted by the propagation model. Let $L = \{L_j\}_{j=1:N}$ the set of measured values; where N represents the total number of measurement points of L. K^j is a possible solution vector to our optimization problem and M_i the column vector defined by equation. The evaluation function of the particles K^j will be:

$$f_{\text{cost}} = \min\left\{\frac{1}{N}\sum_{i=1}^{N}\left(L_i - \left(K^j \times M_i\right)\right)^2\right\} \tag{11}$$

2) *Acceptation criterion for an optimized propagation model*

RMSE is a quadratic scoring rule that measures the average magnitude of the error. An optimized propagation model is accurate if the square root of the mean square error between the actual and prediction measurements is less than 8 dB.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(L_i - \left(K^j \times M_i\right)\right)^2} \tag{12}$$

4. Results

The parameters set for the implementation of DE on the data obtained in the city of Bertoua, are the following:

- $N = 60$, the number of chromosomes in the population at each generation;
- $T = 50$, the maximum number of iterations;
- $Tc = 0.7$, the probability of crossing;
- $F = 0.6$, the scaling factor.

The model will be considered accurate if the RMSE between the measurement campaign data and the predicted data is less than 8 dB (RMSE < 8d B). We obtained different results for each target area. These results are represented by curves with the following legend:

✓ The black graph represents the path losses measured in the field;
✓ The red graph represents the losses obtained from the model optimized by DE;
✓ The green graph represents the losses obtained from the model optimized by linear regression;
✓ The blue graph represents the losses obtained from the Okumura-Hata model;
✓ The yellow graph represents the losses obtained from the free space model.

1) *Results in Bertoua CRTV*

Figure 6 shows the output of the three reference models including the actual measurements. The Okumura-Hata, free space and the new model are compared with the measured data. It is clearly seen that the new model is more accurate than the other models. Moreover, we note a complete and perfect superposition with the model obtained by the linear regression. This demonstrates the reliability of this new model.

Table 5 below shows a comparison of the RMSE value for each of the models considered.

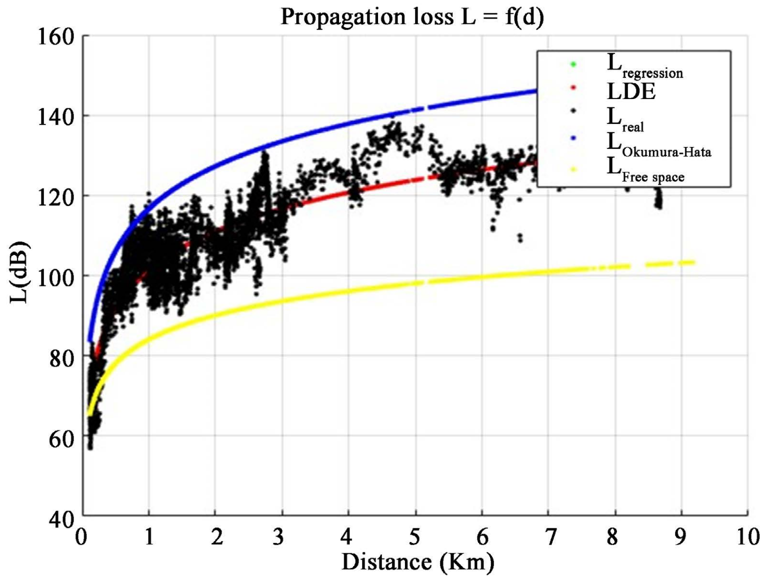

Figure 6. Actual Bertoua CRTV vs predicted measurements.

Table 5. Comparison of RMSE for Bertoua CRTV.

Area	Results	K_1	K_2	K_3	K_4	K_5	K_6	RMSE
Bertoua CRTV	DE	122.43	41.89	0	−4.25	−13.82	−6.55	6.2647
	RL	125.42	41.89	−2.49	0	−13.82	−6.55	6.2647
	Okumura-Hata	137.00	44.90	0	0	−13.82	−6.55	17.2081
	Free-space	83.99	44.90	0	0	0	0	21.4445

We note that the RMSE < 8 dB for the new DE-optimized model, in contrast to the RMSEs obtained with the Okumura-Hata and free-space models which are well above 8 dB. This confirms the accuracy of the new model and demonstrates that our optimization was well done. Figure 7 below shows the evolution of the RMSE per iteration. After 20 iterations, we notice the convergence of the algorithm.

2) *Results in Bertoua Central*

Figure 8 presents the results for the case of Bertoua Central and Table 6 shows the different value of *K* parameters obtained and the value of the RMSE.

Figure 9 below shows the evolution of the RMSE by iteration. After 16 iterations, we notice the convergence of the algorithm.

3) *Results in Bertoua Lycée*

Table 7 presents the *k* values obtained and the RMSE for each propagation model.

Figure 10 presents the results obtained in Bertoua lycée area, while Figure 11 shows the evolution of the RMSE by iteration. After 17 iterations, we notice the convergence of the algorithm.

4) *Summary of results*

In the 3 area above, the RMSE obtained by the new model built using the

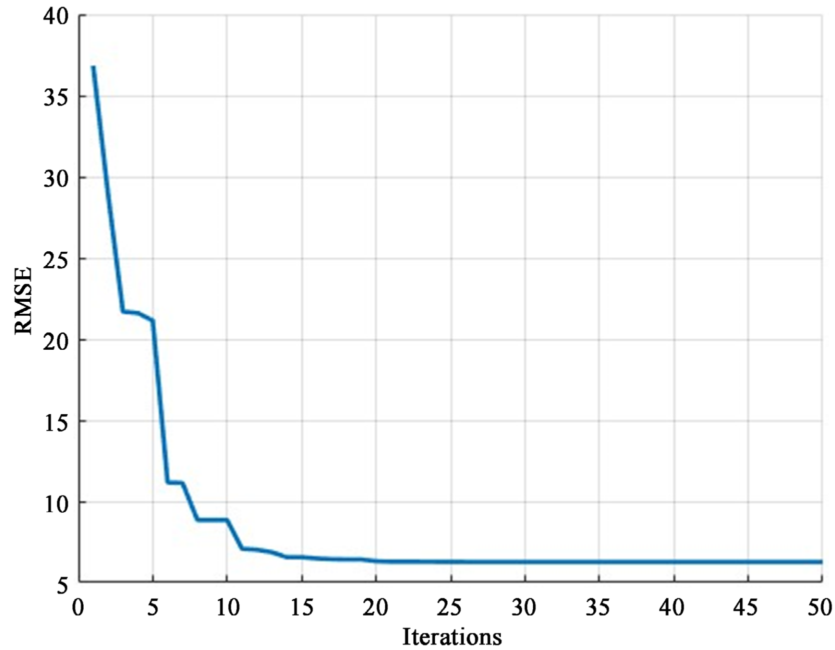

Figure 7. Evolution of RMSE by iteration.

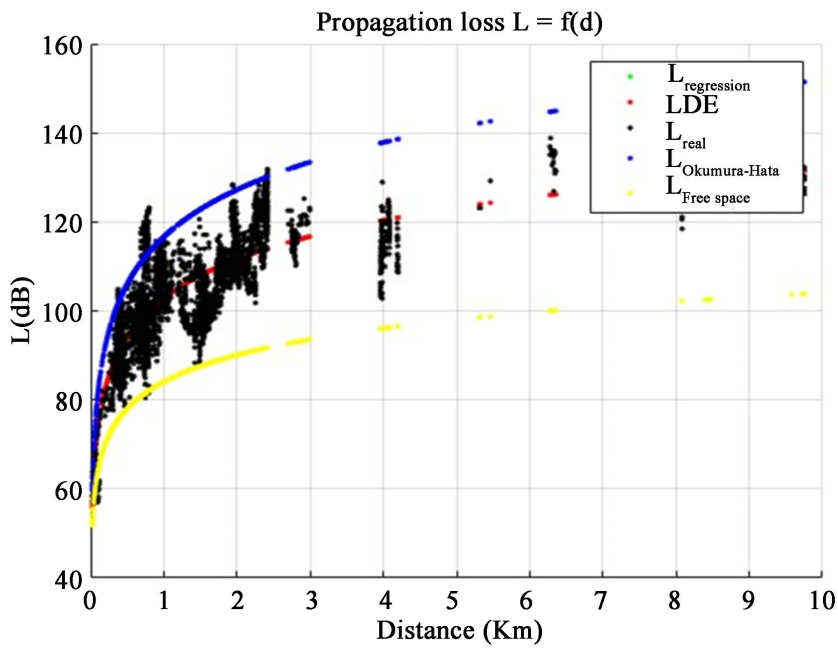

Figure 8. Actual Bertoua Central vs predicted measurements.

Table 6. Comparison of RMSE for Bertoua Central.

Area	Results	K_1	K_2	K_3	K_4	K_5	K_6	RMSE
Bertoua central	DE	120.44	38.73	1.6368	2.04	−13.82	−6.55	7.1049
	RL	126.99	38.73	−2.49	0	−13.82	−6.55	7.1049
	Okumura-Hata	137.0	44.9	0	0	−13.82	−6.55	15.8720
	Free-space	83.99	44.9	0	0	0	0	20.7063

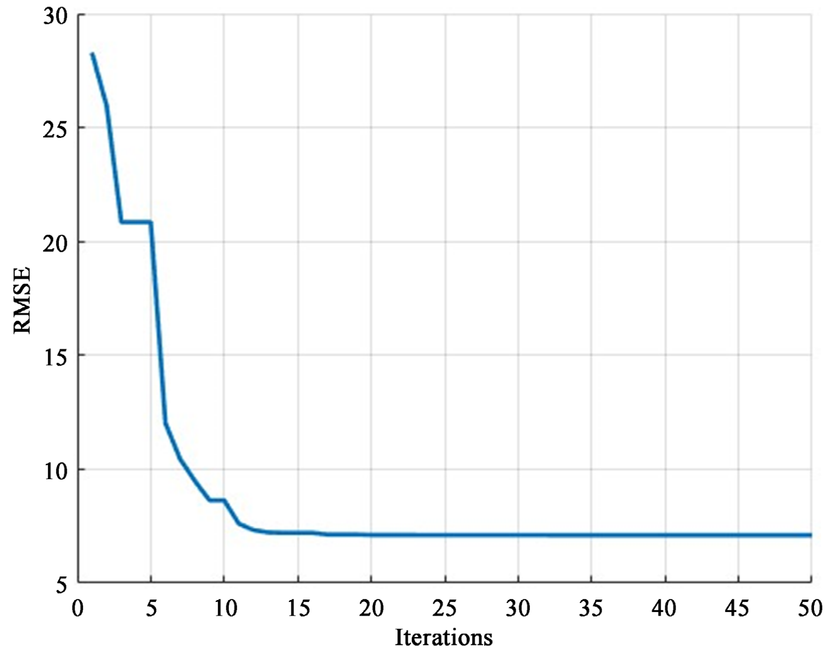

Figure 9. Evolution of RMSE per iteration.

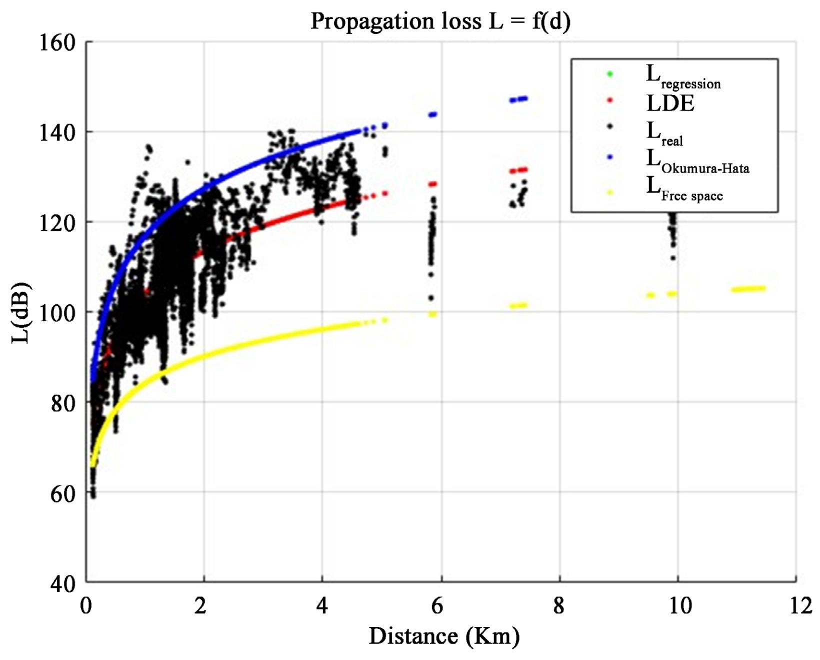

Figure 10. Actual Bertoua Lycée vs predicted measurements.

Table 7. Comparaison des RMSE pour Bertoua Lycée

Area	Results	K_1	K_2	K_3	K_4	K_5	K_6	RMSE
Bertoua Lycée	DE	125.56	41.51	−0.07	−6.98	−13.82	−6.55	7.6717
	RL	127.95	41.51	−2.49	0	−13.82	−6.55	7.6717
	Okumura Hata	137.00	44.90	0	0	−13.82	−6.55	15.3309
	Freespace	83.99	44.90	0	0	0	0	22.9364

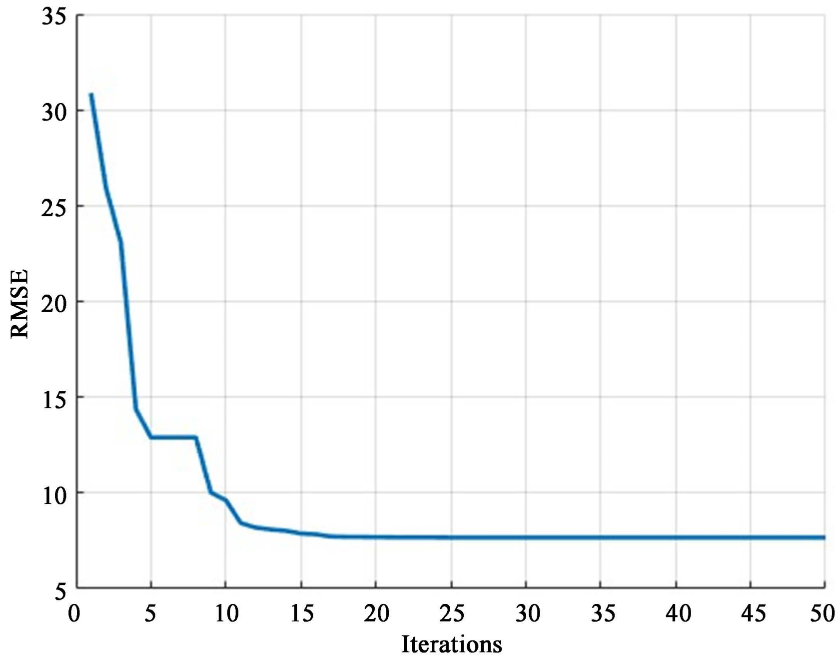

Figure 11. Evolution of RMSE per iteration.

Table 8. Final chromosome selected as new propagation model.

	Method	K_1	K_2	K_3	K_4	K_5	K_6
Solution	Differential Evolution	122.81	40.71	0.53	−3.06	−13.82	−6.55

Differential Evolution algorithm is always less than 8 dB compare to the one of Okumura Hata and free space where the RMSE values are greater than 15 dB, this shows that the proposed model is more accurate compare to the standard model of Okumura Hata and free space. The solutions thus obtained for each area represent the best chromosomes of the population obtained after 50 generations (Gmax = 50). Moreover, in the 3 area considered, we obtained a fast convergence of the algorithm after less than 20 iterations, while running the algorithm 50 times, this also shows that DE can have a fast convergence and will need less processing time and resources. For the whole city of Bertoua, by retaining only the chromosomes having given an RMSE < 8 dB, we can deduce an average chromosome (average value of the chromosomes retained by district). The final result and the corresponding formula are given in **Table 8**.

The final expression of the propagation model that we propose for the city of Bertoua is therefore the following:

$$\begin{aligned} L = {} & 122.8135 + 40.7096 \times \log(d) + 0.5303 \times H_m + (-3.0606) \times \log(H_m) \\ & + (-13.82) \times \log(H_b) + (-6.55) \times \log(H_b) \times \log(d) \end{aligned} \tag{19}$$

This study also showed that linear regression, although the most used optimization method by authors around the world; justified by the number of publications related to it, only allows the optimization of two parameters out of a set of six parameters (the other four being assumed constant). However, the new approach presented allows, if needed, to optimize up to six parameters.

5. Conclusion

At the end of our study, the objective was to show that DE can optimize propagation model used for network planning and that a propagation model adapted to a targeted environment can be obtained by combining the standard K factor model with 6 coefficients, radio measurements collected in this environment and an appropriate processing, in this paper, the processing is based on DE algorithm. The city of Bertoua was chosen as the case study. To do so, we exploited the data from Drive Test carried out in 3 districts of downtown Bertoua, then we took into account the generic model with 6 coefficients, to which we applied the Differential Evolution algorithm. In order to evaluate the new model obtained, we compared its RMSE to that of the Okumura-Hata and free space models. The results obtained after our optimization in the 3 areas were very satisfactory. With the new model, we obtained an RMSE lower than 8 dB in the 3 areas, contrary to the Okumura-Hata and free space models whose RMSE were largely above the 8 dB threshold. These results therefore validated the new model and justified its accuracy. The Differential Evolution optimization algorithm thus proved to be a powerful algorithm for propagation model optimization.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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