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Analysis and Optimization of 4G / LTE Network Pathloss using Particles Swarm Optimization Algorithm

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ABSTRACT- This paper aims to optimize the pathloss in 4G/LTE networks obtained by empirical Radio Frequency (RF) propagation models to enhance user access quality. The radio wave propagation models are mainly used to predict the pathloss which are necessary for planning and optimizing wireless communication systems. In this paper, we propose a parametric optimization for loss estimation in a 4G/LTE network leveraging the Particle Swarm Optimization (PSO) algorithm to enhance the performances of this type of networks and decrease their complexity. For this sake, comparison and performance analysis were conducted using different environments such as urban, sub-urban and rural areas. First, we provide an analysis of radio propagation models, namely: Okumura-Hata, Stanford University Interim (SUI) and Ericsson 9999 models that would be used for outdoor propagation in LTE. Then, we optimize these empirical models using the PSO algorithm to make them more appropriate to the desired coverage area. This is achieved by minimizing the Root Mean Square Error (RMSE) between the optimized predicted data and the measured data in the field. Specifically, the measurements are taken in an urban region, as a case study, the city of Tebessa located in Algeria was selected. The proposed PSO pathloss optimization method showed better prediction performance with lower RMSE values than the analytical method based on empirical pathloss models.

Keywords: 4G/LTE, Pathloss, Propagation Models, Network Coverage, Optimization, PSO.

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1. INTRODUCTION

The fourth generation (4G) wireless network aims to improve spectral efficiency and boost the handling capacity of mobile devices in a single cell. It also provides users with improved speed while ensuring seamless network transitions, minimizing service disruptions during handover, and facilitating the switch to all-IP [1-11]. The architecture of the Long-Term Evolution (LTE) system is built on Internet Protocol (IP), making it specifically designed for efficient packet transmission support. The LTE cellular network infrastructure comprises the E-UTRA/E-UTRAN radio interface and the core network, also known as the Evolved Packet Core (EPC). The EPC includes gateways, mobility management, and the subscriber database. The radio interface and EPC allow the LTE mobile users to connect to external data networks such as the Internet. Unlike 2G and 3G networks, which separate voice and data networks, all media are transmitted as IP packets in an LTE network. The LTE base station (Evolved Node B: eNode B) connects to the EPC via the Serving Gateway (S-GW), and the EPC connects to the packet network via the packet data network gateway (PDN-GW) [3-9]. Wireless systems continue to grow and evolve to meet the demands of increasing traffic following the rapid deployment of 4G LTE networks and 5G wireless systems and beyond [1-30]. For this reason, the analysis and evaluation of 4G LTE network performance is becoming crucial. This later has many advantages that will keep it going long after 5G becomes widespread, so 4G LTE and 5G may coexist for at least a decade [5]. Although 5G is better in many ways, but it does not yet have the coverage to exist on their own without the backbone of the 4G LTE network and all it provides. Hence, the focus on LTE pathloss optimization is relevant due to its widespread, especially in areas where 5G and 6G infrastructure are not yet available. The 4G radio network coverage planning and sizing are achieved by choosing, among different propagation models, the most appropriate model in terms of reliability which requires the network radio coverage optimization, as well as the improvement of the quality (coverage, transmission) of mobile network services. The main goal of propagation modelling is to predict the attenuation of signals, commonly known as Pathloss, as accurately as possible, allowing the range of a radio system to be determined before installation [1-18]. Pathloss propagation models are key elements of planning because they allow to give an estimate range of each cell in an outdoor environment based on output power, signal strength and ratio to noise and interference (SINR). The pathloss is calculated based on the sensitivity of the receiver. This information can be used to determine the received power that allows to identify the maximum possible data rate that can be transmitted. The pathloss is a major component in the analysis and design of the link budget of a telecommunication system, in practical cases; it is calculated by means of various approximations and statistical methods. Selecting a suitable radio propagation (RF) model is essential for long-term wireless networks (LTE) since this later describes the behaviour of a signal as it moves from its source to its destination, and offers a correlation between the transmitter/receiver distances and the pathloss which allows to understand the maximum cell range and the allowed pathloss. The operating frequency, atmospheric conditions, indoor and outdoor surroundings, and the distance between the transmitter and receiver are some of the variables that affect pathloss. In Wireless Communication, there are several empirical or statistical models suitable for the outdoor environment macrocell and microcell [6-19], such as: Okumurra-Hata [20-21]; Stanford University Interim (SUI) [23-24]; Ericsson 9999 [21, 25], etc.

There are several common parameters across propagation models that effect the overall performance, such as antenna gain, transmission power, and loss, frequency of operation, distance between transmitter and receiver, transmitter antenna height, receiver antenna height, and terrain type. An optimized solution is required in order to use efficiently the spectrum to improve coverage, capacity and Quality of Service (QoS). However, the performances of traditional models were inconsistencies observed if we used the specific model in different environments and scenarios for the modeling of propagation pathloss. Recently, many new methods have been introduced to predict propagation models for wireless communications. These later were conducted based on machine learning to improve the efficiency and robustness of wireless communication systems; such as, fuzzy systems, Artificial Neural Network (ANN), Support Vector Machine (SVM), deep learning architectures and global optimization algorithms such as Genetic Algorithm (GA) and PSO [26-31]. The optimization approach proposed in this study makes use of Particle Swarm Optimization (PSO) algorithm for setting the best parameters of Okumura-Hata and SUI models to make them more appropriate to the geographic environment. This algorithm has gradually become more popular among researchers and has shown to deliver excellent results in a variety of application domains. The primary benefit of PSO is that it requires less parameter tuning [32]. Furthermore, this later not only produces a solution, but a set of possible solutions, from which the best one is selected [32-35]. An optimized solution is required in order to use efficiently the spectrum to improve coverage, capacity and Quality of Service (QoS). In this study, the analysis of predicted and measured pathloss over urban environment of the city of Tebessa, located in Algeria, is presented. The propagation measurements were carried out at a frequency of 1800 MHz. The reminder of this paper is organized as follows. *Section 2* is devoted to the analysis of RF propagation models in LTE and the optimization of the pathloss models using PSO algorithm. Simulation results and comparison are presented in *Section 3*. Some concluding remarks are presented in *Section 4*.

2. BACKGROUND AND 4G/LTE PATHLOSS OPTIMIZATION

In addition to offering a greater range of services, 4G wireless networks also make wireless services more effective, scalable, and dependable. The main goal of choosing the appropriate Radio Frequency (RF) model is to ensure the QoS. The propagation model can be used in several system performance aspects such as handoff optimization, power level adjustments, and antenna placements. No propagation model can be considered for all variations experienced in wireless networks; it is necessary to experiment several models for determining the pathlosses. In this study, three models were considered in outdoor propagation, namely Okumura-Hata, Stanford University Interim and Ericsson 9999.

2.1.Okumura-Hata Pathloss Model

The Okumura-Hata Model [20] is the most frequently used model, based on several measurements of RSS signal taken in the Tokyo area. This model takes into consideration several factors, primarily, the nature of the environment by specifying its degree of urbanization (urban, dense urban, suburban, rural). This model is designed to predict the propagation pathloss under operation frequency ranging from 150 up to 1500MHz. The pathloss according to this model for, respectively, urban and rural environments is given by *equations (1) and (2)* [16-22].

$$PL_{urban} = 69.55 + 26.16\log_{10}(h_m) - a(h_m) + [44.9 - 6.55\log_{10}(h_b)]\log_{10}(d) \quad (1)$$

with $a(h_m) = [1.1\log_{10}(f) - 0.7]h_m - [1.5\log_{10}(f) - 0.8]$

$$PL_{rural} = PL_{urban} - 4.7[\log_{10}(f)]^2 + 18.33\log_{10}(f) - \alpha \quad (2)$$

where PL_{rural} and PL_{urban} stand for total Pathloss (dB), f: Carrier frequency (MHz), d: Distance between mobile station and BTS (Km), h_b, h_m : Height of BTS and mobile station (meters) and α : Ranges from 35.94 for countryside regions and 40.94 for desert regions.

2.2 Stanford University Interim Pathloss Model

SUI is a model developed by Stanford University [23-24], it is used for frequencies above 1900 MHz and designed for three different types of terrain or areas. This propagation pathloss model is formulated by equation (3) [23-24].

$$PL = A + 10\,\gamma\,log\left(\frac{d}{d_0}\right) + X_f + X_h + S \quad for\; d > d_0 \quad (3)$$

with d: distance between the transmitter and the receiver, d_0: reference distance (set to 100 meters), X_f : frequency correction factor, X_h: base station height correction factor, A: free space pathloss $A = 20\,log\left(\frac{4\pi d_0}{\lambda}\right)$($d_0$:is the distance between T_x na R_x; ; λ :is the wavelenght), γ: pathloss exponent and S : Shadowing factor. The pathloss weakening exponent is described as exponent:

$$\gamma = a - bh_b + \frac{c}{h_b} \quad (4)$$

where h_b is the height of the base station and a, b *and* c are terrain factors listed as shown in. The correction factor for frequency and base station height for various terrains is given by:

$$\begin{cases} X_f = 6\,log\left(\frac{f_c}{2000}\right) \\ X_h = 10.8\,log\left(\frac{h_r}{2000}\right) \quad \text{for terrain A and B} \\ X_h = 20\,log\left(\frac{h_r}{2000}\right) \quad \text{for terrain C} \end{cases} \qquad (5)$$

: height of the receiver antenna in meters. The shadowing factor is given by:

$$S = 0.65\,(log(f_c))^2 - 1.3\,\log(f_c) + \alpha \qquad (6)$$

with $\alpha = 5.2$dB for rural and suburban environments (terrain A and B) and 6.6 dB for the urban environment (terrain C), see *table 1*.

Table 1. Parameters of different terrain for SUI model

Model Parameters	Terrain A	Terrain B	Terrain C
a	4.6	4	3.6
B	0.0075	0.0065	0.005
C	12.6	17.1	20

2.3.Ericsson 9999 Pathloss Model

The Ericsson model is provided by Ericsson Company for use in planning wireless networks [21-25]. This model is an extension of the Okumura-Hata model modified to consider different propagation environments according to the parameters indicated in *table 2*. The Ericsson pathloss is formulated by *equation (7)*.

$$PL = \alpha_0 + \alpha_1 log\,(d) + \alpha_2 log(h_b) + \alpha_3 log(h_b)\,log(d) - 3.2[log(11.75 \times h_b)^2] + 44.9\,log(f_c) - 4.78\,(log(f_c))^2 \qquad (7)$$

with $\alpha_0, \alpha_1, \alpha_2, \alpha_3$: parameters set according to the environments.

Table 2. Settings of parameters α_n according to the environments for Ericsson 9999 Model

Environment	α_0	α_1	α_2	α_3
Rural	45.95	100.6	12	0.1
Suburban	43.20	68.63	12	0.1
Urban	36.20	30.20	12	0.1

2.4 4G/LTE Pathloss Optimization

The current pathloss models present many drawbacks. Effectively, these later are frequently generic and might not adequately depict contexts or environments. For this reason, their forecasts may not be entirely accurate and cause problems when put into practice [13, 14, 25-28]. Furthermore, pathloss models frequently make assumptions about perfect circumstances and fail to consider dynamic phenomena. To improve the current pathloss models, we used a PSO algorithm to overcome the limitations caused by static assumptions. For this, we develop a more robust and accurate optimized model based on real measurement data of a specific environment and frequency.

The PSO algorithm is developed by Eberhart and Kennedy in 1995 as one of random optimization strategies [33]. This strategy is inspired from social psychology and dynamic behaviour of insects, birds and fish schooling. PSO method becomes one of the most used for solving continuous and nonlinear optimization problems [32-35]. The objective of our approach is to use real measurements to optimize the Okumura-Hata and SUI models' parameters in order to obtain a prediction with high precision and accuracy, and provide effective and stable connection in the coverage area. The used algorithm can be easily implemented in a real-valued case study to optimize the pathloss via a fitness-function. Each particle of the swarm represents a potential solution in the research space of the optimum. Let $\vec{X_i}(t)$ the position and $\vec{V_i}(t)$ the velocity of the particle P_i at time t, defined by *equation (8)*.

$$\begin{cases} \vec{X_i}(t) = \vec{X_i}(t-1) + \vec{V_i}(t) \\ V_{ij}\,(t) = \omega\,V_{ij}\,(t-1) + c_1.rand1[P_{bestij}(t-1) - X_{ij}(t-1)] \\ \qquad + c_2.rand2[g_{bestj}(t-1) - X_{ij}(t-1)] \end{cases} \qquad (8)$$

with $i = 1, 2, \ldots, Np$; $j = 1, 2, \ldots N_d$; where Np : Number of swarm particles, N_d: Number of problem variables (particle dimension). $V_i(t)$ stands for the velocity of a particle in each iteration, $X_i(t)$ the particle position at each iteration, c_1 and c_2 are acceleration constants (c_1 controls the cognitive behaviour of the particle and c_2 controls the social ability of the particle), $rand_1, rand_2$ represent random numbers, P_{bestij} is the *jth* component of the best position occupied by the i^{th} particle of the swarm recorded in previous iterations, g_{bestj} is the j^{th} component of the best position occupied by the best overall particle of the swarm, and ω is the inertia weigh coefficient updated in each iteration and given by *equation (9)*.

$$\omega(iter) = \omega_{max}\,\frac{\omega_{max} - \omega_{min}}{iter_{max}}\,iter \qquad (9)$$

with $iter$: the rank of the current iteration, ω_{max} : the initial value of the inertia weigh coefficient generally set to 0.9, ω_{min}: the final value of the inertia weigh coefficient set between 0.3 and 0.4. The purpose of introducing the inertia weigh is to achieve a balance between local research and global research commonly known as exploitation and exploration. To adapt the empirical pathloss model to our case study, specifically, the city of Tebessa; in our work, we focus on the choice of two empirical models namely: Okumura-Hata and SUI. The pathloss prediction is mapped to an optimization problem with constraints. Each problem is formulated as a parametric equation with n parameters to be adjusted using the PSO algorithm by minimization of the error, in terms of RMSE, between the predicted pathloss and the real measurements. Formally, the optimization problem is given by *equation (9)*

$$\begin{cases} fitnessfunction(X_{in}) = PL(X_i) \quad with\ X_i = (k_{i1}, k_{i2}, \ldots, k_{in}) \\ \qquad \min PL(k_{i1}, k_{i2}, \ldots, k_{in}) \\ until\ RMSE(PL_{real}, PL) \le \varepsilon \end{cases} \qquad (9)$$

The n-factors propagation model of Okumura-Hata is a function of five variables defined by *equation (10)*.

$$PL_{urban} = k_1 + k_2 \log_{10}(f) - k_3 \log_{10}(h_m) - a(h_m) + [k_4 - k_5 \log_{10}(h_b)] \log_{10}(d) \quad (10)$$

whereas, the SUI model is defined by Equation (11) with four variables.

$$PL = A + 10k_1 \log_{10}\left(\frac{d}{d_0}\right) + k_2 + k_3 + k_4 \quad (11)$$

Algorithm (1) describes the steps of the proposed approach.

Algorithm (1): ***4G/LTE Pathloss Optimization using PSO***

Step 1: Choose $iter_{max}$, Acceleration constants (c_1, c_2: $0 \le c_1 \le 2$ and $0 \le c_2 \le 2$)

Step 2: Randomize the positions $k_1, k_2, .. k_n$ and the particle velocities with distributed values.

Step3: Evaluate the objective function $min(PL(k_1, k_2, .. k_n))$ at each position X_{ij}^0

Step 4: For $iter$ in range(0, $iter_{max}$); Evaluate the Inertia weigh coefficient $\omega(iter) = \omega_{max} \frac{\omega_{max}-\omega_{min}}{iter_{max}} iter$ ($\omega_{max} = 0.9$ and $\omega_{min} = 0.3$)

Step 5: Determine $fitnesfunction(X_{in}) = PL(X_i)$ and evaluate the objective function associated with each of the position and update the position and velocity of each particle. If the value of the position X_{ij} is better than its current P_{bestij} ; then P_{bestij} takes this new value. If the best value P_{bestij} is better than current g_{bestj}, then g_{bestj} is replaced by this best value and the position is stored.

Step 6: Check the stop criterion each time. If the constraint is not satisfied, go to step 3, otherwise the parameter values $X_i = (k_{i1}, k_{i2}, \dots, k_{in})$ have been found and the associated patlhloss is determined $PL(X_i) = PL\ (k_{i1}, k_{i2}, \dots, k_{in})$.

In *Algorithm (1)*, P_{bestij} stands for the j^th component of the best position occupied by the i^th particle of the swarm recorded in the previous iterations (particle best); g_{bestj}: the j^th component of the best position occupied by the global best particle of the swarm. The Root Mean Square Error (RMSE) is useful in many contexts, but it's especially useful for regression analysis and assessing models that generate numerical predictions [36]. RMSE was calculated between measured Pathloss value and those predicted by empirical or measured model using *equation (12)* [27-37]

$$RMSE = \sqrt{\sum \frac{(PL_m - PL_r)^2}{N-1}} \quad (12)$$

where PL_m stands for the measured pathloss (dB); PL_r the predicted pathloss (dB); N the number of measured data.

3. RESULTS AND DISCUSSIONS

3.1. Pathloss Propagation simulation Results

The pathloss is calculated using the mathematical equations given previously for the RF propagation models. *Figure 2* depicts the resulting attenuations between eNodeB and the mobile terminal for the encapsulated models using MATLAB.

In our calculations, we considered different parameters such as carrier frequencies, distance between transmitter and receiver, height of receiver and height of the base station. The simulation parameters of the propagation models were set as follows:

- *Distance (d): from 0 up to 10Km ;*
- *Frequency (fc): 1800MHz and 2100MHz;*
- *Height of eNodeB (Hb1): 10 m and 30 m;*
- Mobile terminal height (Hm): 1.5 m.

The real measurements are taken in the city Tebessa located in Algeria. The 4G/LTE local operator Mobilis eNodeB N°12668 is located in the urban area named *1^er Novembre 1954* under the coordinates: N35◦25′34′′ and E8◦3′42′′ covering a radius of 2.5 km. The location of the eNodeB is depicted in *figure 1*.

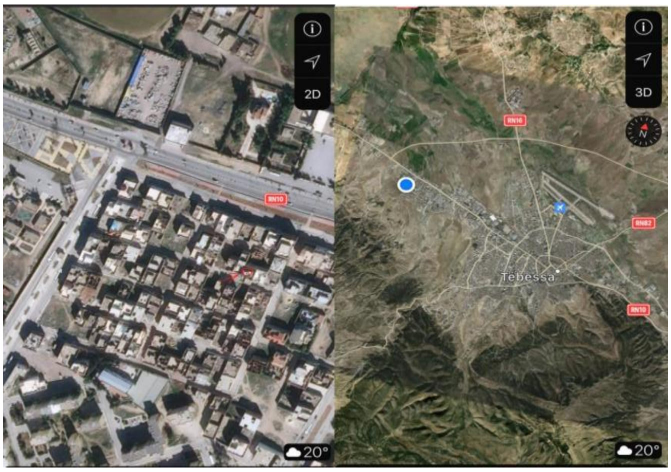

Figure 1. Satellite image of the location eNodeB N° 12668 (Google Map)

In Following, eNodeB heights were alternately set to 10m and 30m. *Figure 2 and 3* depict the obtained results in terms of pathloss for Okumura model with frequencies 1800 MHz and 2100 MHz respectively. *Figure 4* depicts the effects of frequency on the propagation pathloss, the results were obtained for different environments and frequencies ranging from 900 up to 2100 MHZ. We note that there is a proportional relation between the attenuation and the used frequency, and an inversely proportional relation between the eNodeB height and the attenuation: *i.e.*, if Hb increases the pathloss propagation decreases.

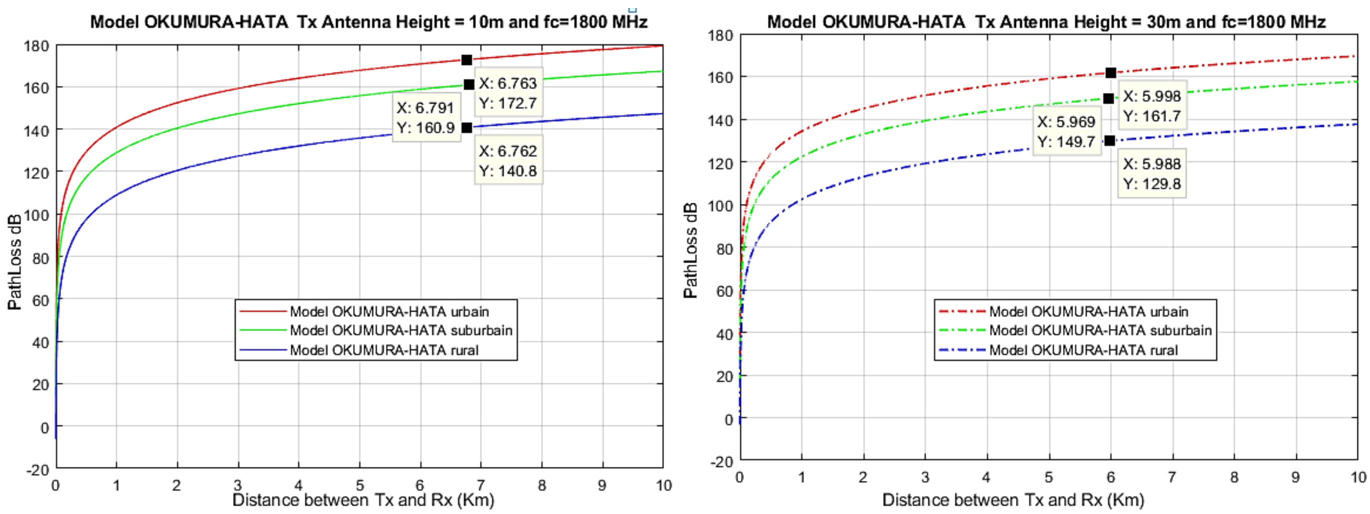

Figure 2. Okumura Model Pathloss results with 1800 MHz and Tx antenna height=10 and 30 meters for three different environments.

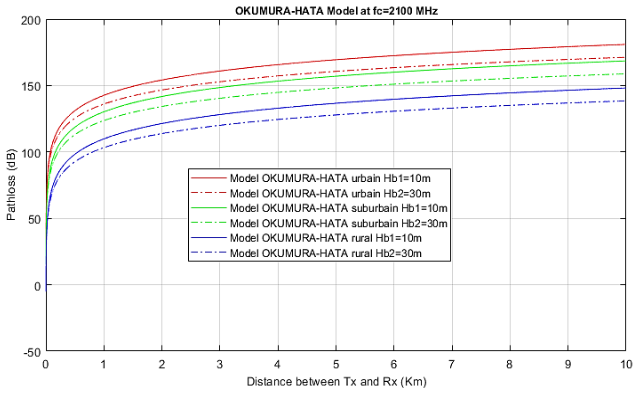

Figure 3. Okumura Model Pathloss results with 2100 MHz and Tx antenna height=10 and 30 meters for three different environments.

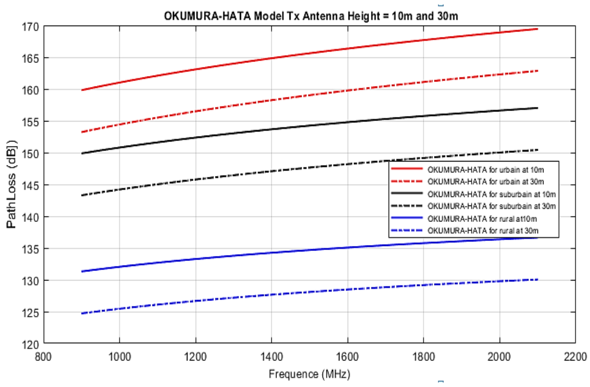

Figure. 4. Influence of the frequency range variation on the Okumura-Hata propagation pathloss.

Following the same experimental protocol and with the same parameters. The obtained plots of propagation pathloss for the SUI (see *figure 5*) and Ericsson (see *figure 6*) models as a function of distance, then as a function of frequency for the different environments (urban, suburban, rural) are shown in the following figures. *Figure 6* depicted the pathloss and the influence of frequency variation for the Ericsson 9999 model.

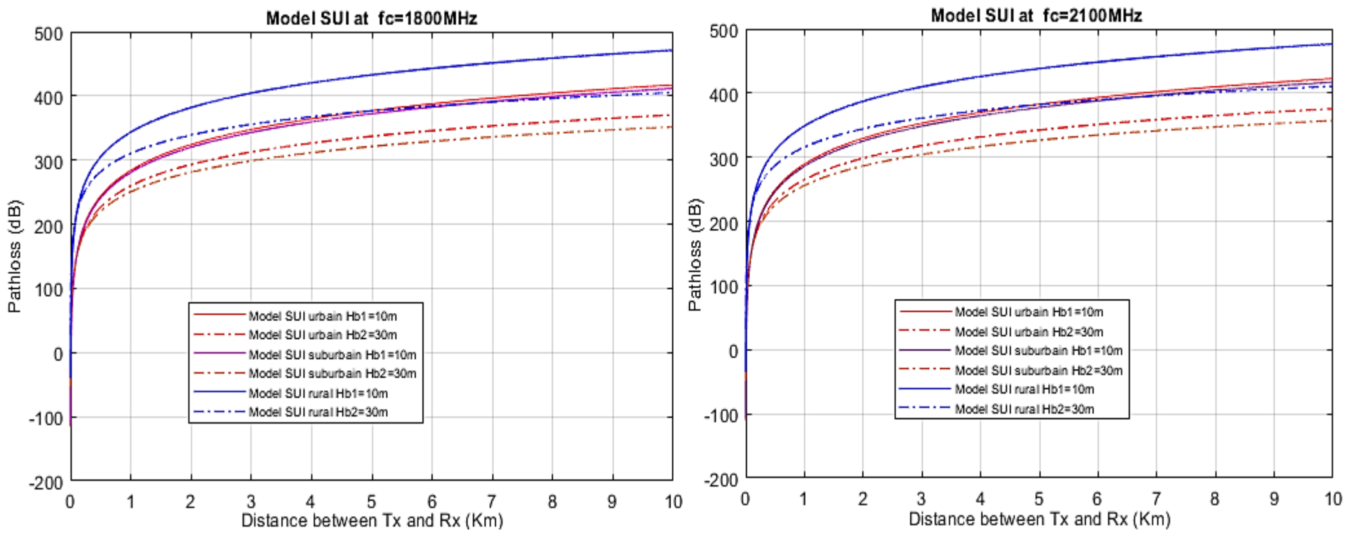

Figure 5. Simulation results of the propagation pathloss for SUI model with 1800 MHZ and 2100 MHZ for two eNodeB heights Hb1 = 10m and 30m and terrains A, B and C

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As findings, after comparing the pathloss results found for the three types of environments for Okumura-Hata and SUI models, we note that the attenuation increases if we increase the frequency and decreases if the height of eNodeB is increased. Unlike previous models, the Ericsson model attenuation decreases when increasing frequency, and rises when increasing eNodeB height. Okumura-Hata model gives low pathloss for the three environments (urban, suburban and rural), between 138 and 180 dB compared to SUI and Ericsson models (351 to 476 dB and 228 to 413 dB respectively), which makes it more efficient than the other empirical models.

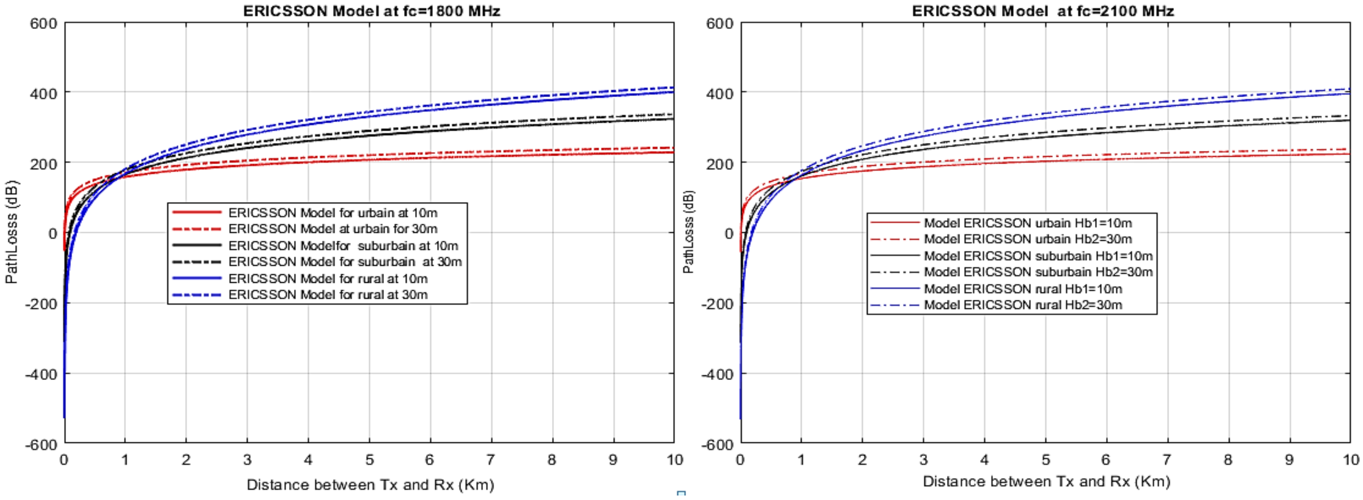

Figure 6. Ericsson 9999 Model simulation for two frequencies 1800MHz and 2100MHz.

3.2. Optimization of pathloss models using PSO algorithm

3.2.1. Optimization of the Okumura-Hata model using the PSO algorithm in urban area

In the field of wireless communication systems, particularly in urban and suburban settings, the Okumura-Hata model is a commonly used empirical model for pathloss prediction. The problem to be solved is formulated as a single mathematical equation with five variables $(k_1, k_2, k_3, k_4, k_5)$. These variables must be defined in such a way to make this model appropriate for the coverage in urban area of the 4G/LTE network with the 1800 MHz frequency band. The K-factor propagation model is defined by *equation (10)*. The k_i parameters values depend highly on the type of terrain and the characteristics of the propagation environment. The proposed protocol uses the PSO algorithm to optimize the K-factor model to adapt it to the physical environment of the antenna shown in *Figure 1*. In the simulation, the stop criterion of PSO is the minimum of the RMSE. *Table 3* illustrates the obtained results for five iterations (Niter=5). Each parameter of the PSO algorithm has an important influence on the behaviour of the particles and therefore on the convergence of the algorithm. Even if the PSO method presents satisfactory results, the choice of the right parameters remains a critical task. Note that, a simple change of parameter value can highly affect the results and can even lead to premature convergence. *Figure 7* shows a comparison between the empirical Okumura-Hata model and the results obtained for the K-model with 5 iterations and different particle sizes. It can be seen that the choice of optimization parameters with 30 particles and 5 iterations, gives a better approximation of the model with a minimum error value compared to the other settings.

Table 3. PSO optimization results for Okumura-hata pathloss model Niter=5 and different particle numbers

Number of particles		**30**	50	100	150	200	250
RMSE		**0,62**	13,74	6,38	0,87	2,31	11,43
Model parameters	k_1	**38,63**	61,64	27,31	28,92	40,89	42,50
	k_2	**36,65**	38,06	37,52	44,57	48,76	32,56
	k_3	**52,62**	46,61	78,51	64,67	52,04	79,63
	k_4	**15,09**	8,19	41,08	24,96	13,18	45,10
	k_5	**15,55**	36,76	6,63	29,83	50,37	2,41
Execution time (s)		**6,12**	11,35	19,30	28,44	38,13	47,91

Following the same experimental protocol, *figure 7* depicts the results obtained by varying the number of iterations (Niter = 5 and Niter = 100). *Table 4* presents a comparative study between the two best obtained parameters. We notice that, in terms of execution time, the combination (k1 = 38.63, k2 = 36.65, k3 = 52.62, k4 = 15.09, k5 = 15.55) gives the best model with an execution time of 6.123 s.

Table 4. Optimization comparison results of the pathloss model using the PSO for the Okumura-Hata model

Number of iterations		5 iterations	100 iterations
Number of particles		30	100
RMSE		0,62	1.34
Model parameters	k_1	38,63	26,99
	k_2	36,65	50,06
	k_3	52,62	70,11
	k_4	15,09	31,00
	k_5	15,55	41,63
Execution time (s)		6,12	316,10

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It is worth noting that, the best pathloss predicted model compared with the mathematical model Okumura-Hata in terms of mean squared error is given by the following set of parameters (see *Figure 8*)

- k_1 = 38.63, k_2 = 36.65, k_3 = 52.62, k_4 = 15.09, k_5 = 15.55 *for Niter = 5 and Nparticles = 30;*
- k_1 = 26.99, k_2 = 50.06, k_3 = 70.11, k_4 = 31.04, k_5 = 41.63 *for Niter = 100 and Nparticles = 100.*

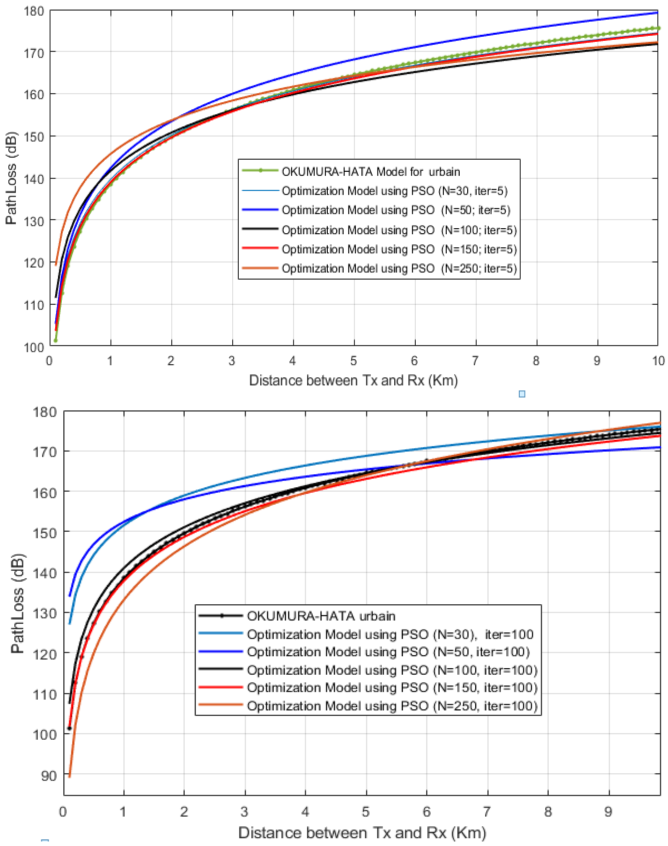

Figure 7. Optimization Okumura-Hata pathloss using PSO algorithm with Niter=5 and 100 with Nparticles = 30, 50,100,150, 250

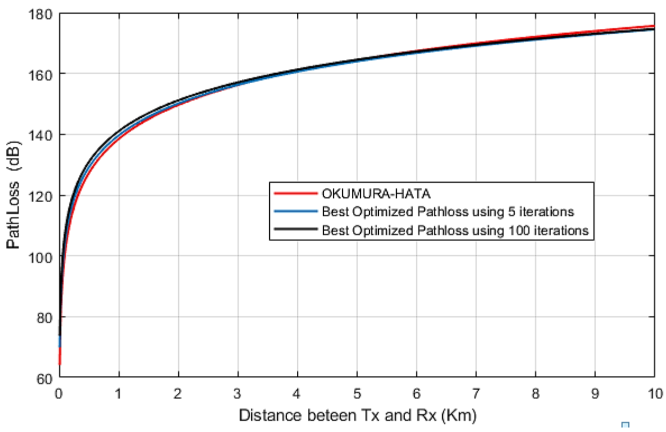

Figure 8. Comparison between the Okumura-Hata model and the best optimized pathloss model

3.2.2. Optimization of the SUI model using the PSO algorithm in an urban area

Following the same experimental protocol and keeping the same PSO parameters. We optimized the SUI propagation model by opting for an empirical K-factor model with four parameters. *Equation (11)* represents the model to be predicted. After several tests, we select the best combination with 70 particles and 15 iterations, the obtained parameters are: k_1 = 5.32; k_2 = 0.45; k_3 = 82.33 and k_4 = 24.97 with a minimum RMSE=2.892 and an execution time equal to 18.237 s. The obtained results, representing the comparison between the empirical mathematical model of SUI in an urban environment and the predicted SUI model based on the PSO, are illustrated in *figure 9*. From what follows, we conclude that the optimization based on PSO is very efficient and effective in terms of pathloss model parameters optimization. The overall results of the two empirical models Okumura-Hata and SUI, show clearly that the former gives the best optimization results with the lowest overall error and execution time compared to the SUI model.

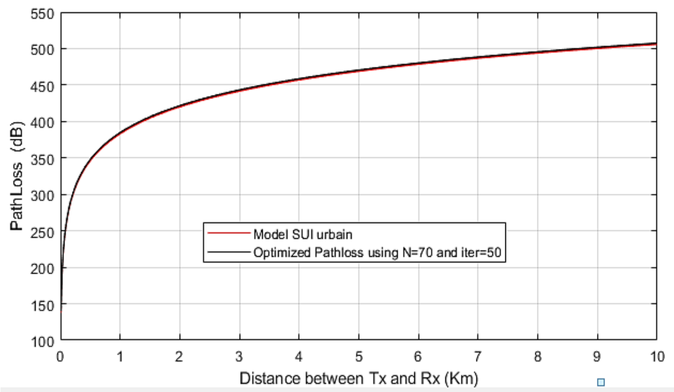

Figure 9. Pathloss comparison between the empirical and the optimized SUI models with Niter = 15 and Nparticles = 70.

Table 5 presents a comparison between the best obtained performances.

Table 5. Obtained optimization results for the Okumura-Hata and SUI models

Model	Number of iterations	Number of particles	RMSE	Execution time
Okumura-Hata	5	30	0,6344	6,12
SUI	25	70	2,8924	18,24

3.3. Optimization of Okumura-Hata and SUI models with real measurements using the PSO

In the following simulation, real measurements were taken for the eNodeB of Tebessa city of the operator Mobilis located in the urban area. The site specifications are as follows

- *Type of region: urban;*
- *Transmitter height (eNodeB): 15 m;*
- *Receiver height (mobile): 1.5m;*
- *Frequency: 1800 MHz.*

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The measurement of signal strength was obtained by using the G-NetTrack ProAndroid application in Tebessa city environment with a frequency of 1800 MHz. The reference signal received power (RSRP) is measured and recorded for 5 to 500 meters between the mobile antenna and the transmitter at a near constant mobile antenna height of 1.5 m. To calculate the attenuation in dB we used the LTE link budget for the downlink as follows:

$$MLB(dB) = EIRP - RSRP$$

where MLB stands for the maximum pathloss, $EIRP$: the Effective Isotropic Radiated Power (dBm) and $RSRP$: the mean reference signal received power (dBm). In the first step, we simulate the empirical pathloss models Okumura-Hata, SUI and the real measured data for a graphical comparison. The flowchart of the proposed system is presented in *figure 10*.

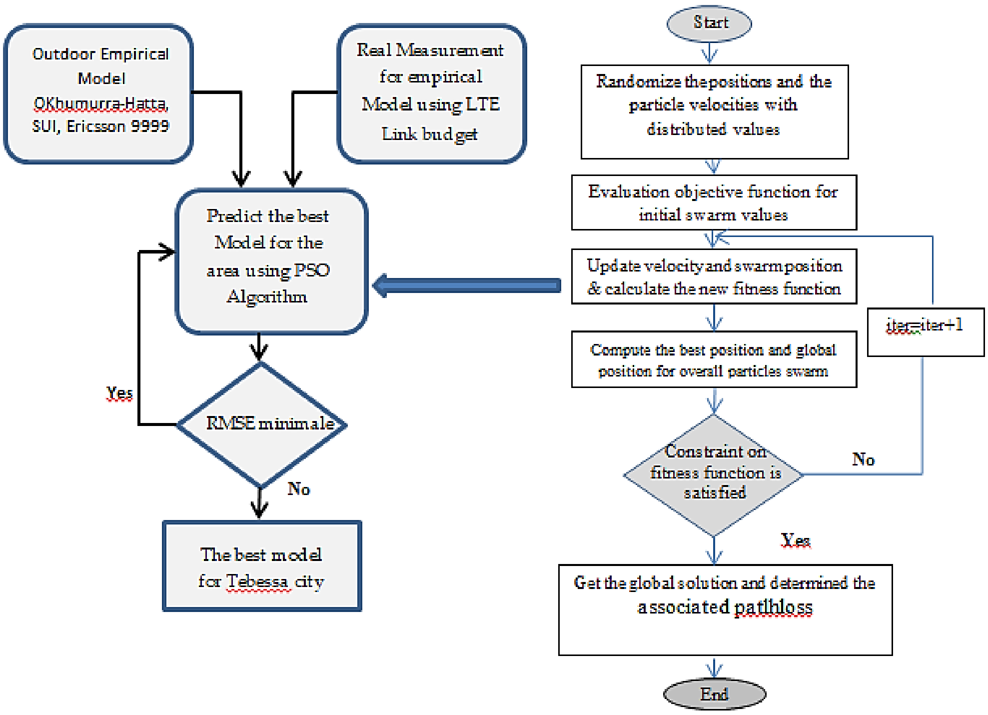

Figure 10. Flowchart of the proposed system based on PSO algorithm for pathloss prediction

Then, we calculate the squared error for the two empirical models with the real measurements. *Table 6* shows the obtained RMSE for each used model and the real measurements.

Table 6. Results of RMSE between empirical models and real measurements in the region of Tebessa (eNodeB N° 12668)

Empirical Model	Okumura-Hata	SUI
RMSE	60,51	49,65

From *figure 11* and *table 6*, we notice that the SUI model has a minimum overall error value of 49,65 and 60,51 for Okumura-Hata model. Hence, the SUI predicted pathloss model approximates in terms of attenuation the real measurements.

In order to improve the performance of empirical pathloss models and make them as close as possible to real measured data for Tebessa city, we used the PSO algorithm to optimize the empirical pathloss model for acurate prediction in the LTE network. Accordingly, to *figure 11*, Tebessa City's measured pathloss levels range from 152 to 185 dB. For the standard pathloss models, the Okumura-hata and SUI models vary between 52 and 129 dB and between -6 and 217 dB, respectively.

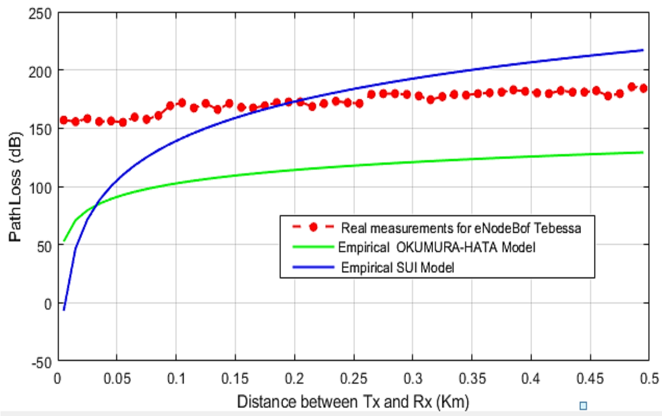

Figure 11. Comparison of the empirical Okumura-Hata and SUI models with the real measured data in eNodeB N°12668 of Tebessa.

To make the Okumura-Hata or SUI model more adapted to the real measured values. We opt for the use of the same protocol of the PSO optimization algorithm for a K-parameter model. After several tests and by varying the number of particles and the number of iterations, the optimal obtained results are presented in *table 7*.

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Table 7. Optimization comparison results of the pathloss model using the PSO for the Okumura-Hata model

Empirical Model		Okumura-Hata	SUI
Number of particles		70	70
Number of iteration		25	25
RMSE		13,21	23,60
K parameters	k_1	40,07	4,87
	k_2	55,70	0,60
	k_3	34,70	67,50
	k_4	6,00	30,54
	k_5	39,69	/
Execution time (s)		55.22	49,26

The results obtained using PSO optimizations are presented in *figure 12*. The results demonstrate that the developed model fitted the measured loss values obtained from the studied location with high efficiency. The suggested approach outperforms the traditional analytical technique grounded in Okumura-Hata and SUI models with respect to convergence velocity, computing effectiveness, and algorithmic stability. Compared to the SUI model, whose global error value is equivalent to 23.60, the Okumura-Hata model exhibits a minimum global error value of 13.21. We have used the PSO algorithm to fine-tune the parameters of the Okumura-Hata empirical model to bring it as close as possible to the real measurements, while also adapting it to the eNodeB site in the city of Tebessa, even though the SUI model was closer to the real attenuations measured in terms of error.

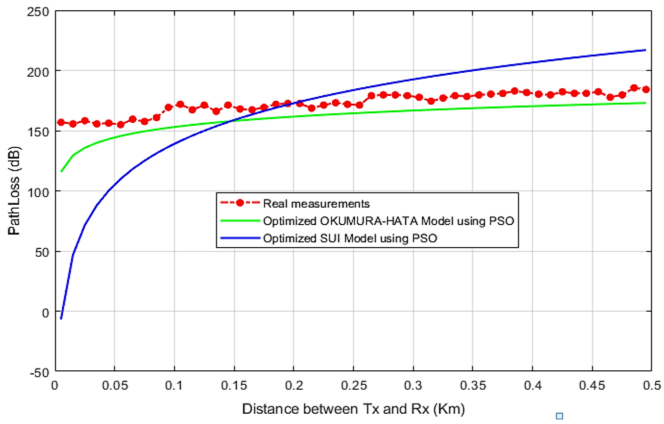

Figure 12. Graphical comparison between optimized Okumura-Hata and SUI models with the real measured data and optimized K parameters.

The proposed PSO optimization method showed good prediction performance with lower RMSE values.

4. CONCLUSIONS

In this paper, several empirical propagation models have been described and investigated for their performance for wireless communication and optimal coverage with lowest power consumption. In order to design efficient wireless communication systems, we assessed the performance of selected pathloss models and compared them with pathloss based on propagation measurements in various environments. The pathloss of measured data from 4G/LTE operator Mobil is eNodeB N° 12668 located in Tebessa city was compared with existing predictions models, specifically, Okumura-Hata and the SUI models. In the first part of the simulation, we studied three empirical macro-cell models and the influence of a set of their parameters, such as: the mode of propagation, the variation in the distance between the transmitter and the receiver, the height of the eNodeB and the frequency, on the performance of the 4G / LTE radio link system. The results show that the type of environment in which electromagnetic waves propagate directly affect the attenuation. In case study, the empirical Okumura-Hata model showed better robustness and performances. The results show that the choice of system parameters and environmental parameters influence the pathloss value. In the second part, we proposed to use a metaheuristics method to determine the optimal parameters of the empirical model to enable optimal prediction of pathloss. The predicted and optimized Okumura-Hata model using PSO algorithm, was found to be the most accurate for Tebessa city environment and was found to be satisfactory for the environment. Future research can take many directions, all of which can have significant effects on important indoor and outdoor applications. In order to develop the future dense wireless communication infrastructures for a 4G & 5G co-existing networks, the validated pathloss model must be used with measurement-based approaches and comparative validation procedures for different higher frequencies.

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